

# **COMPUTER AIDED PATTERN RECOGNITION AND VISUAL INTERPRETATION OF MSS IMAGERY**

by

**A. S. R. K. V. MURALI MOHAN**



DEPARTMENT OF CIVIL ENGINEERING  
**INDIAN INSTITUTE OF TECHNOLOGY KANPUR**  
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for the Degree of  
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by  
**A. S. R. K. V. MURALI MOHAN**

to the  
**DEPARTMENT OF CIVIL ENGINEERING**  
**INDIAN INSTITUTE OF TECHNOLOGY KANPUR**  
**JULY 1986**

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CERTIFICATE

This is to certify that the present work entitled  
"Computer Alived Pattern Recognition & Visual Inspection  
of M.S.B. Imagery" has been carried out by Mr. Murali Rao  
Ajaykumar S.R.K.V. under my supervision and is not produced  
anywhere for the award of a degree.

July, 1986

(Dr. K.K. RAMPAL)

Professor  
Department of Civil Engineering  
Indian Institute of Technology  
Kanpur

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## ABSTRACT

Supervised Spectral Pattern Recognition and Visual Interpretation of MSS Imagery are two parts that constitute this thesis work. In pattern recognition, soils and surface features of the Krishna-Godavary delta bearing orbit index No. 142-049 are classified using K-Class algorithm. Various combinations of the 4 MSS bands are tried to achieve the best results. It is observed that a combination of more than two MSS bands gave very unsatisfactory results. Further, a line printer map based on K-Class Classifier decisions is prepared showing three surface features viz. agricultural, waterbodies and built-up area. The area occupied by each of the above classes is precisely determined.

In the latter part, keys are developed for visual interpretation of MSS imagery to prepare soil-classification map, built up area map and surface drainage map. It also explores the possibilities for salinity survey, turbidity studies and study of river characteristics using satellite imageries. Also, the lineaments present in the area and a Rose diagram to find their frequency azimuthal variations are drawn. For mapping purposes using visual interpretation techniques, Band-2 imagery ( $0.5 - 0.6 \mu\text{m}$ ) is found to be extremely useful.

## CHAPTER - I

## INTRODUCTION AND OBJECTIVES

1.1 General

October 1957 marked the beginning of the space age with the launch of SPUTNIK by USSR. For the first time in history, a man-made object was circling the earth, covering different regions and countries of the world from its vantage point in space. The years following the launch of Sputnik were the Cold War years with each super power trying to dominate the other in space. This led to rapid development of satellite borne sensor for reconnaissance purposes. Today, one has lost count of satellites that spy the earth every moment for military and civilian purposes.

The civilian remote sensing programme was essentially an US and USSR effort in the seventies. U.S.A. made the data from their satellites available to many countries around the world at extremely reasonable costs. As a consequence the use of such data has become common the world over. With the advent of high resolution satellites like French SPOT System, remote sensing techniques are being reliably applied in many a number of fields. A number of studies like crop pattern determination, crop estimation, landuse, surface water distribution, river course monitoring, forestry planning, geological mapping, fishing habitat characteristics etc. are being taken up.

Here in India, we have various facilities like data products laboratory at Space Applications Centre (SAC), full-fledged acquisition and processing facility at NRSA, Hyderabad for undertaking various projects for diverse applications. The launch of Indian Remote Sensing Satellite (IRS-1), no doubt, gives the indigenous efforts a further boost in this field.

#### 1.2 Satellite -- its products

The data obtained from satellites is converted into a variety of data products such as high density digital tapes (HDDT), 70 mm film, microfiche, black and white as well as-color prints, computer Compatible Tapes (CCT) and false color composites (FCC) by four different levels of processing. At first level browse products are generated in the form of HDDT and film negatives for all the bands after eliminating the cloud covered areas through quick look data. This product will be corrected for radiometric and earth rotation effects, annotated with salient details. The standard products are generated at level -2, that are corrected for sensor scene and platform-related geometric effects. Precision products are generated at level-3, and special products at level-4. Special products like floppy diskettes, use standard products (such as CCT) as inputs and are generated for specialized user needs for specific applications.

The data products systems include image processing computers,

special photographic laboratories equipped with systems for processing, developing, and printing of both B & W and color photographs and sophisticated recorders like laser beam recorder.

### 1.3 Applications -- techniques

Remote Sensing has proved its worth in a myriad of applications. Indian Scientists at various well equipped research organisations and frontline academic Institutes have applied the satellite products for diverse applications geological, agricultural, landuse, animal husbandry with diverse techniques- computer -aided, visual and image processing.

Snow melt run-off studies (Ramamoorthi, 1983), ground water table prediction studies (Rampal, 1984), soil mapping (Karale et.al, 1983), forest survey and management (Madhavan Unni, 1983), land evaluation and classification for agriculture (Murthy, Venkataratnam and Saxena, 1983) are few to quote among Indian Works. Deekshatalu and Krishnan, 1983 presents an overview the basic research problems in remote sensing in a discipline oriented approach.

### 1.4 Acquisition of Satellite Data

MSS data of Landsat-4 has been acquired for the present study. Landsat-4 was launched on July 16, 1982 and carried the Thematic Mapper (TM) and Multi Spectral Scanner (MSS). The TM

collects radiometric data in seven spectral bands and has a ground pixel resolution of 30 m in the non-thermal bands (120 m in the thermal band) compared to the four spectral bands of MSS and low resolution of 80 m. Landsat -4 TM data cannot be acquired at the Indian Landsat Earth Station (ILES), situated at about 60 KM from Hyderabad, A.P., due to the failure of X-band radio channel in Feb, 1983 which is responsible to transmit the TM data directly to ground stations. The MSS, however, has not been affected as it uses a separate S-band radio channel. Landsat-5, launched on March 1, 1984, supplies both MSS and TM data. This space craft is positioned on the World Reference System (WRS) with its cycle offset 8 days from that of Landsat -4.

The attitude of Landsat 4 and 5 (705 KM) compared to that of Landsat 1, 2 and 3 (910 KM) means that a different WRS path-row number is used to refer the nominal scene centre. While the row number remain same, path numbers are 10 to 12 lesser than those for the first three satellites. The MSS bands of Landsat 1, 2 and 3 are numbered 4, 5, 6 and 7 while those of the latter two are 1, 2, 3 and 4. The TM spectral bands are numbered from 1 to 7. The RBV subscenes are numbered as A, B, C and D. The spectral ranges of these bands, resolutions and their major applications are listed in Table 1.1.

The products obtained for the study are of the scene with index number 142-049. A CCT, black and white paper prints, films

TABLE 1.1 : SPECTRAL BANDS AND SIGNIFICANCE

SENSE R	SPECTRAL BANDS	RESOLUTION	APPLICATION
<b>LANDSAT MSS</b>			
BAND - 1	0.5 - 0.6 um	80 m	Qualitative discrimination of depth and turbidity of standing water bodies.
BAND - 2	0.6 - 0.7 um	80 m	Delineation of topographic and cultural features.
BAND - 3	0.7 - 0.8 um	80 m	Shows tonal contrasts for various land-use categories.
BAND - 4	0.8 - 1.1 um	80 m	Land-water discrimination.
<b>LANDSAT THEMATIC MAPPER</b>			
BAND - 1	0.45 - 0.52 um	30 m	Increased penetration into water bodies, soil/vegetation and deciduous/coniferous flora discrimination.
BAND - 2	0.52 - 0.60 um	30 m	Vegetation, vigor assessment
BAND - 3	0.63 - 0.69 um	30 m	Chlorophyll absorption band for vegetation discrimination, for contrast between vegetation and non-vegetation features.
BAND - 4	0.76 - 0.90 um	30 m	Biomass content and delineating water bodies.
BAND - 5	1.55 - 1.75 um	30 m	Vegetation/soil moisture content and snow/cloud differentiation.
BAND - 6	2.08 - 2.35 um	30 m	Discriminating rock types and hydrothermal anomalies.
BAND - 7	10.40 - 12.50 um	120 m	Thermal IR band for vegetation stress, soil moisture and thermal mapping.

of Bands 1, 2 and 4 are obtained from NRSA. Band-3 print and film were not obtained because of non-availability.

The video data obtained on CCT is in Binary mode, 32-bit format which is not Dec system- 1090 Compatible. Dec is a 36-bit Word machine. The obtained tape is formated for 32-bit word machines like Vax, IBM and PDP series. If the tape is tried on DEC-10, it tries to read the four bits of the next word and thus tampering the data. As a remedy to this problem, a dummy blank was padded after 4th, 9th, 14th.... bytes resulting in the increase of the record size from 3596 to 4500 bytes. This was carried out by Nagaraju (1986) with the help of CMC people. This conversion can be carried out with DEC-10 also with the help of CHANGE.EXE, a system program. This program is given in the Appendix-1 succeeded by various switches that may be used in the program. It should be borne in mind that DEC-10 cannot support 800 BPI tapes and so they cannot be tried for a change in their format. DEC-10 which accomodates only 1600 BPI tapes reads the 800 BPI tapes at a speed twice of what is desired. NRSA supplies both varieties of tapes and 1600 BPI tapes only may be acquired for the local use.

### 1.5 Objectives of the Study

The following objectives are envisaged in the present study, the study area being Krishna-Godavari delta having an orbit index No. 142 ~ 049. Two techniques are employed to achieve these objectives viz. supervised spectral pattern recognition (K-Class Classifier) and visual interpretation techniques using MSS data and paper prints.

With K-Class Classifier using the signals of four MSS bands:

- (1) to classify the soils of the region
- (2) to classify the surface features such as water bodies, agricultural area, built-up area etc.
- (3) to prepare a line printer map based on the classifier decisions showing the surface features.

With visual interpretation of three MSS prints:

- (1) to prepare a soil classification map
- (2) to delimit the built-up area in the delta zone
- (3) to update the drainage map of the area
- (4) to draw the lineament map of the study area.

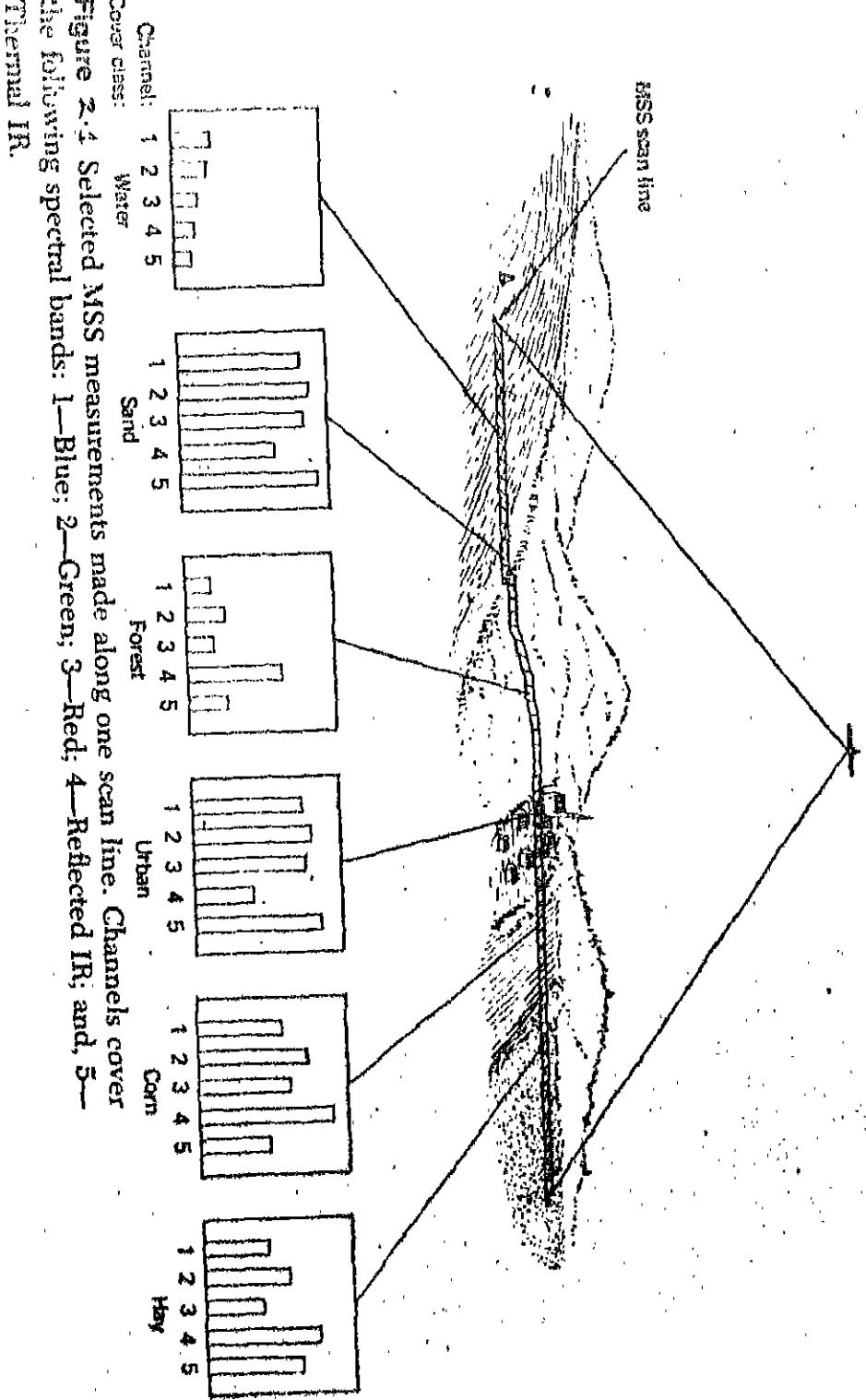
## CHAPTER II

### PATTERN RECOGNITION USING K-CLASS CLASSIFIER

#### 2.1 Pattern Recognition-Various Stages and Techniques

Spectral Pattern Recognition is a computer aided technique by which MSS digital data may be analyzed quantitatively and automatically. The advantage with this analysis is that digital data of desired bands may be used in any combination. In this process, we use the computer to look at the multiple channels of digital data. By dealing with the image data quantitatively, the spectral information of any number of channels can be fully evaluated.

The concept of representing MSS data in a numerical format is illustrated in Fig. 2.1. The figure shows MSS measurements of certain features in a landscape made along one scan line. The digital values or spectral responses of these features in five bands are represented with vertical bars. If these spectral patterns are sufficiently unique for each feature type, they may form the basis for an automated interpretation of the image data using a spectral pattern recognition procedure. There are various techniques available to analyse and classify a set of data into groups or classes. These techniques can be broadly divided as supervised and unsupervised pattern recognition methods. The difference between the two is that the former needs a training set



**Figure 2-4** Selected MSS measurements made along one scan line. Channels cover the following spectral bands: 1—Blue; 2—Green; 3—Red; 4—Reflected IR; and, 5—Thermal IR.

of data acquired with human knowledge.

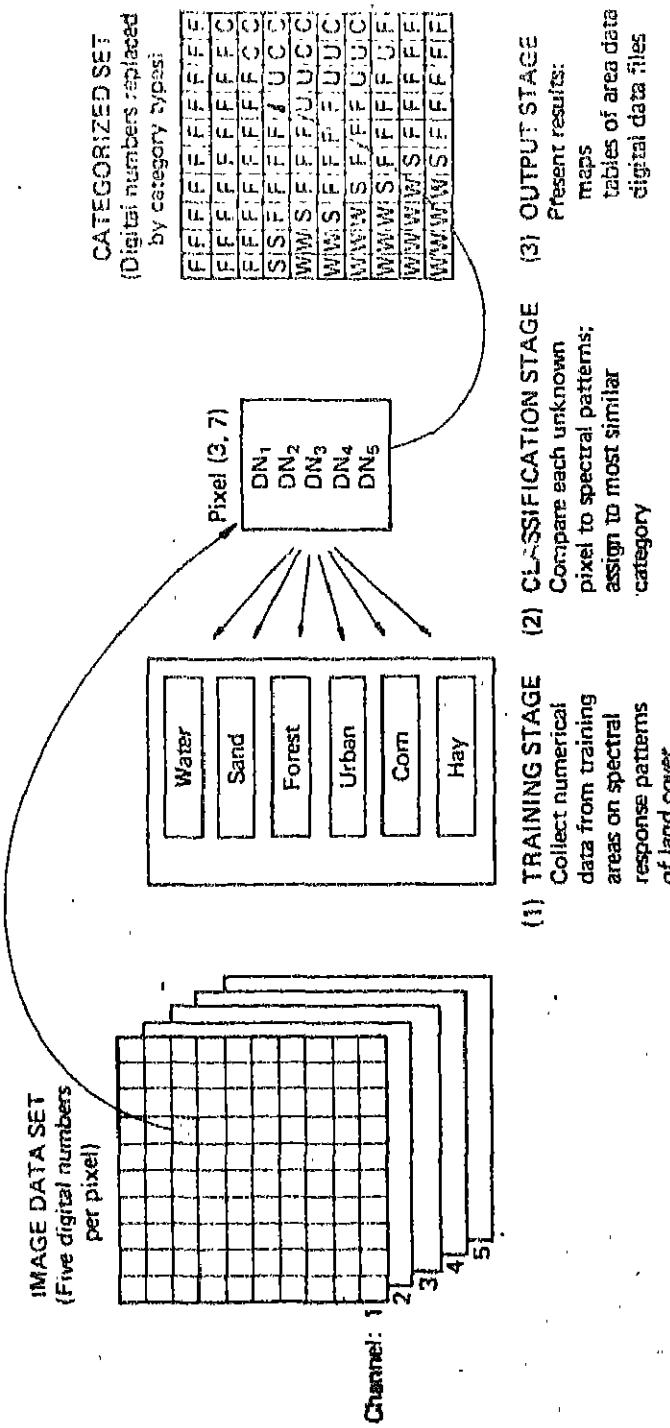
In unsupervised classification methods the mode seeking algorithm is employed to classify the data into groups of points or clusters of similar spectral characteristics. Hence collection of representative training sets is circumvented. In class-room analogy, these methods are learning with and without teacher.

The three basic steps involved in typical supervised pattern recognition procedure are 1) training stage , 2) classification stage, 3) output stage. This is illustrated in Figure 2.2.

The training stage, a requisite process in supervised classification, involves compilation of an 'interpretation key' for each feature type of analyst's interest.

To arrive at the key, the analyst should have the knowledge of the "training areas" or "training sites" wherein the features of one's interest are contained. These may be termed as representative sample sites of known cover type. The digital data at these areas are retrieved from Computer Compatible Tapes (CCT's) to form the training set.

In the classification stage, each pixel in the image data set is compared to each category in the numerical interpretation key. This comparison is made numerically, using any one of a number of different strategies to decide which category an unknown pixel value "looks most# like".



**Figure 2.2.** Typical spectral pattern recognition process.

Each pixel is then labeled with the name of the category it resembles, or labeled "unknown" if sufficiently similar to any category. The category label assigned to each pixel is then recorded in the corresponding cell in an interpreted data set. Thus, multi-dimensional digital data is used to categorise the area of interest. After the entire data has been categorized, the results will be presented in the output stage, commonly in the form of a map. This way, we are also able to enlarge the imagery without the loss of detail or continuity.

Because it is numerically based, spectral pattern recognition is largely an automated process. In this respect, visual image interpretation and spectral pattern recognition are complimentary procedures.

Another classification of pattern recognition techniques is parametric and non-parametric methods. In parametric methods each pattern class is characterised by a statistical distribution which in turn is dependent on certain number of parameters. The non-parametric methods do not assume any such distribution. Table 2.1 gives a partial list of classification methods. Two of the methods are briefly described here.

## 2.2 (a) Bayes' Classifier

One of the most widely used parametric classifiers is the Bayes' Classifier. In parametric classification a probability

TABLE 2.1 : A PARTIAL LIST OF CLASSIFICATION METHODS\*

Classification Method	Categorization 1	Categorization 2	Comments
Bayes	Supervised	Parametric	Minimizes "average risk" of misclassification. Requires knowledge of a priori probabilities of occurrence of each class.
Maximum Likelihood	Supervised	Parametric	Minimize average risk of misclassification when the probabilities of occurrence of each class are equal. When the conditional density functions are assumed Gaussian, this is a quadratic classifier used, for example, in ID3MS.
K-Nearest Neighbour	Supervised	Nonparametric	Finds class assignments of K-nearest neighbors and puts given samples in the majority class.
Prototype	Supervised	Nonparametric	Represents each class by a prototype and assigns a point to nearest prototype type (e.g. minimum distance classifier used in ORSER).
Linear	Supervised	Nonparametric	Linear classifier is a general term to encompass techniques which use linear surfaces (hyperplanes) to separate classes. There are several iterative methods for deriving such hyperplanes.
Piecewise Linear	Supervised	Nonparametric	This is a generalization of linear classifiers. Useful when the classes are not separable by hyperplanes (either pairwise or individually from all other classes). The parallel epiped classifier is a particular case of this method.
Quadratic and Higher Order Polynomials	Supervised	Nonparametric	Use higher order surfaces for separating classes. The surfaces can be found using the same method as for the Linear Classifier by suitable enlargement of the feature vectors.

Contd.....

Distance Based Clustering	Unsupervised	Nonparametric	There are several methods which use distance measures to group data into clusters. These are iterative methods and vary slightly from each other in the details of handling, initiation, and updating of clusters.
Density Based Clustering	Unsupervised	Parametric	Assuming, form of probability density functions, find cluster assignments such that a measure of overlap is minimized.
Density Based Clustering	Unsupervised	Nonparametric	Approximate multivariate density by sample histograms or some other functions and seek their local maxima (modes).
Table Look Up	Both	Both	Can be used to implement any decision rule obtained from any classification method.
Extraction and Classification of Homogeneous Objects (ECHO)	Both	Parametric	Spatial Classifier as opposed to "per pixel" Finds homogeneous spatial areas and then classifies all pixels in each such area into one class.
Layered			Hierarchical (decision tree) approach permitting selection of features classes and classification method at each "node" (branch point).

\* Parametric classifiers assume that samples from each class belong to a population modeled by a probability density function with a few parameters. Typically, a normal (Gaussian) density function is assumed. Non parametric classifiers do not make such assumptions.

density function is assumed and the parameters of that distribution are estimated. Let  $x_1, \dots, x_N$  be random variables where  $x_i$  is the noisy measurements of the  $i$ th feature. Let  $p(x/C_j)$  be the conditional probability density function of class  $j$  and  $p(C_j)$  is the a priori probability of class  $C_j$ . The task of the classifier is to assign the input sample such that the probability of misrecognition is minimized.

The Bayes' decision is that

$$x \in C_i$$

if  $P(C_i)p(x/C_i) \geq P(C_j)p(x/C_j)$ , for all  $j$

Assuming Gaussian distribution with mean vector  $M_i$  and Covariance matrix  $K_i$

$$P(x/C_i) = \frac{1}{(2\pi)^{N/2} |K_i|^{1/2}} \exp \left[ -\frac{1}{2} (x - M_i)^T K_i^{-1} (x - M_i) \right]$$

then the decision boundary between classes  $i$  and  $j$  becomes

$$\log \frac{P(C_i)}{P(C_j)} - \frac{1}{2} \left[ (x - M_i)^T K_i^{-1} (x - M_i) - (x - M_j)^T K_j^{-1} (x - M_j) \right] = 0$$

The above rule is also referred to as the maximum likelihood classification estimation rule (MLE) which has been very popular for classifying remotely sensed data.

## 2.2 (b) K-Class Classifier

The K-Class Classification algorithm developed by Zagalsky (1968) is a supervised and non-parametric pattern recognition method. It is based on the derivation of a transformation matrix (B). The main computing steps are given below. For mathematics and algorithm of the classifier, Serreyn and Nelson (1973), and Sashi Kumar (1982) may be referred to:

### Computing Steps :

- a) Compute the a priori probability  $p_i$  of occurrence of each class i where

$$p_i = \frac{\text{No of points in class } i}{\text{Total no. of points}} ; i = 1, 2, 3, \dots, K\text{-Classes}$$

- b) Calculate the mean of the attributes (signals or grey levels retrieved from CCT) over all classes.

$$\bar{x}_j = \frac{\sum_{i=1}^K (x_j \text{ of class } i) (\text{No. of points in mode } i)}{\text{Total no. of points}}$$

for  $j = 1, 2, \dots, N$  features

- c) Calculate the attributes covariance matrix

$$\phi = [ x \bar{x}^T - \bar{x} \bar{x}^T ]$$

- d) Calculate the inverse of Covariance matrix ( $\phi^{-1}$ )

- e) Calculate the Transformation matrix (B)

$$[ B ] = [ \bar{x}^i - \bar{x} ]^T \phi^{-1}$$

f) Calculate the Vector of Constants (C)

$$[ C ] = [ B ] [ X ]$$

g) Calculate the elements  $d_i$  of the class vector d for the attribute vector  $X$ , where

$$d_i = [ BX - C_i + 1 ] p_i ; i = 1, 2, \dots, K \text{ class}$$

h) Assign the attribute  $X_j$  to class i for which  $d_i$  is maximum

This classifier as a computer program is implemented to various applications in this study. To train the K-Class Classifier the investigator needs to have a training set of data. This set consists of sample data from each class of interest. Then all the above steps are performed. The only unknown in the equations for the decision vector elements is the feature vector to be classified. The decision is calculated by selecting the maximum element value  $d_j$ . The feature vector  $X$  is assigned to Class j. By this procedure, the map of an area can be made representing the classes by different distinct characters.

A brief overview of pattern recognition and image processing is presented by Deekshatulu and Kamat (1984) and Fu (1984). One may refer to these papers for extensive coverage of pattern recognition techniques.

### 2.3 Previous Work With the Classifier

Serreyn and Nelson (1973) applied this technique on data taken from ERTS imagery for classification of follow, Corn and Soyabeans. Lidster et al,(19 )applied multiple regression, mode seeking, and K-Class classification analyses for correlating digital data of Landsat and Aircraft imagery with Water table depths in irrigated agriculture. The mode seeking, and K-Class classification analysis of a Corn field resulted in the correct classification of 91 % of water tables. Sashi Kumar (1982), employed the algorithm to find the number of classes that occur in a two dimensional classification with the groundwater table depth and the Band = 7 spectral reflectance for the alluvial portions of U.P. and Rajasthan.

### 2.4 Applications of the K-Class Classifier

The classifier is put to variety of uses in the present work such as soil identification,surface feature identification, and mapping with the help of classifier. Each of these applications is dealt in detail in subsequent sub-sections. Various combinations of bands are tested to see how they respond to the classifier.

#### 2.4.1 Soil Identification

The study area consists mainly three types of soils viz; Recent

alluvium (sedimentary unconsolidated) sandstone (sedimentary consolidated) and unclassified crystalline rocks as it turned out from visual interpretation of satellite imagery. The classes chosen for this are Recent alluvium (black soil of delta area), unclassified crystalline rocks, Khondalites, Coastal Sandy Soils, and Charnockites. The exact locations of the occurrence of these soils are noted from survey of India maps. The geographical Co-ordinates i.e. latitudes and longitudes of these points are converted into scan line numbers and pixel numbers.

The basis for the selection of the above varieties of soils is Khondalite and Charnockite both being crystalline fall in the zone of unclassified crystalline rocks. These two classes are to be shown as separate entities after classification if and only if the place where attributes were obtained for unclassified crystalline rock class contains a different material i.e. other than the above two.

To start with, a 3-class, 2-feature problem is chosen. The term feature here means the data from a band of MSS. The Bands selected are 1 and 2 of MSS (Landsat 4) and the classes are Khondalites, unclassifieds, and Recent alluvium. In each class, eight attributes (pixel values) are retrieved and then subjected to K-Class classification. The results are produced as Table 2.2 The number of signals being same in each class the probability of occurrence of each is given as 0.333. The transformation matrix

## 3-CLASSIFICATION PROBLEM

THE CLASSIFICATIONS ARE :  
KODAKALITE, UNCLASSIFIED CRY., ROCKS, RGC, ALUMINUM, OF GLASS

NUMBER OF SIGNALS = 9 DIVISION = 24 PROBES = 1

THE SIGNALS IN CLASS 1 ARE :

37.00	120.00
30.00	120.00
34.00	120.00
34.00	120.00
37.00	120.00
34.00	120.00
39.00	120.00
37.00	120.00

THE SIGNALS IN CLASS 2 ARE :

40.00	70.00
40.00	70.00
40.00	60.00
44.00	60.00
43.00	70.00
40.00	75.00
49.00	70.00
44.00	70.00

THE SIGNALS IN CLASS 3 ARE :

30.00	67.00
32.00	71.00
32.00	74.00
32.00	78.00
34.00	67.00
32.00	71.00
30.00	70.00
30.00	71.00

NUMBER OF SIGNALS IN CLASS (1) = 8

NUMBER OF SIGNALS IN CLASS (2) = 8

NUMBER OF SIGNALS IN CLASS (3) = 8

THE MATRIX B IS :

0.00334	0.05962
0.16999	-0.01664
-0.17333	-0.04298

## DISCUSSION OF THE DATA

SAMPLE NO.	CLASS	D(1)	D(2)	D(3)	PCT. IN
1	1	1.00	0.07	-0.16	1
2	1	0.97	-0.30	0.33	1
3	1	0.97	-0.07	0.10	1
4	1	0.97	-0.07	0.11	1
5	1	0.97	0.10	-0.07	1
6	1	0.97	-0.07	0.10	1
7	1	0.96	0.21	-0.19	1
8	1	0.97	0.10	-0.07	1
9	2	0.00	1.03	-0.12	2
10	2	-0.01	1.06	-0.05	2
11	2	-0.06	1.07	-0.02	2
12	2	-0.13	0.81	0.32	2
13	2	-0.01	0.77	0.21	2
14	2	0.09	1.03	-0.12	2
15	2	-0.04	1.06	-0.05	2
16	2	-0.03	0.77	0.21	2
17	2	-0.09	-0.06	1.09	3
18	2	-0.04	0.59	0.92	2
19	2	0.05	0.07	0.01	2
20	2	0.13	0.05	0.82	2
21	3	-0.08	0.22	0.05	2
22	3	-0.04	0.59	0.92	2
23	3	0.13	-0.06	0.03	2
24	3	-0.01	-0.02	1.03	2

## CLASSIFIED AS

CLASS	1	2	3
1	6	0	0
2	0	8	6
3	0	0	8

PROBABILITIES = 0.333    0.333    0.333

NO. OF MISCALCULATIONS = 0.

PERCENT CORRECTLY IDENTIFIED OVERALL= 100.00000

## PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION

CLASS	1	2	3
1	100.00	0.00	0.00
2	0.00	100.00	0.00
3	0.00	0.00	100.00

THE BOUNDARY BETWEEN CLASS 1 AND CLASS 2 IS :

$$-0.05555203 \cdot X1 + -0.02542212 \cdot X2 = 0.12106046$$

THE BOUNDARY BETWEEN CLASS 2 AND CLASS 3 IS :

$$0.41444172 \cdot X1 + 0.00877676 \cdot X2 = 5.11398900$$

THE BOUNDARY BETWEEN CLASS 3 AND CLASS 1 IS :

$$-0.05988968 \cdot X1 + -0.03420090 \cdot X2 = -5.23505050$$

is represented by B of size  $(3 \times 2)$ . From the table of decision vectors it may be observed that the value for whichever class is maximum, the decision will be that the signal is attributed to that class. Thus, for the sample No.1, the decision values are 1.09, 0.07, and -0.16. So, the sample is placed in the class 1 thus making the correct identification. The confusion matrix shows that no. of miscalculations is zero (the diagonal elements are 8 each in value). The decision boundaries are shown next in a two-dimensional space.

Next, the attributes of the same three classes are retrieved from Band-2 and Band-3 of MSS to put before the classifier. This time also, the classifier has successfully identified the samples with 100 % accuracy. The results are in Table 2.3.

Having satisfied with the results with the help of 2-band signals, it is tried to test the same classes with the help of Bands 2, 3 and 4 signals. Thus it becomes a 3-class, 3-Feature problem. In each class, eight signals were given as samples to the classifier. Now, it is interesting to see that percent correctly identified has fallen down to 66.67 %. Earlier, in both cases, it was 100 %. The confusion matrix (Table 2.4) shows that the four signals of class (3) are identified with class (1) and the next half with class (2) resulting in a drastic fall of occurring. The examination of the spectral responses of these classes in the three bands may give an explanation for this fall.

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## TABLE II. 2.3

23

### 3-CLASS, 2-FEATURE PROBLEM

THE CLASSES ARE :  
KODDADALITES, UNCLASSTED CRYSTALLINE ROCKS, RECENT ALUVIUM  
ALUVIUM OF BAND 2 & BAND 3

NAME= 3 MPELTS 2 NSTGE= 24 NERUBS= 1

## THE SIGNALS IN CLASS I ARE:

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PERF-SIGNALIS TH CLASS 2 AND 3

75  
134  
135  
136  
137  
138  
139  
140

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#### EXERCICE DE SIGNAIS DE CHASSE (CLS)

WITNESS OF SIGHTING ON CLASS DATE 6

## WILDFIRE SPREAD IN CLOUD FOREST (CONT'D.)

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DECISION BOUNDARIES

THE BOUNDARY BETWEEN CLASS 1 AND CLASS 2 IS :

$$-0.04967626 \cdot x_1 + -0.01997374 \cdot x_2 = 0.31393754$$

THE BOUNDARY BETWEEN CLASS 2 AND CLASS 3 IS :

$$0.14329859 \cdot x_1 + 0.02011641 \cdot x_2 = 4.74299450$$

THE BOUNDARY BETWEEN CLASS 3 AND CLASS 1 IS :

$$+0.05342832 \cdot x_1 + -0.04099215 \cdot x_2 = -5.05693210$$

TABLE 2.4

## 3-CLASS, 3-FEATURE PROBLEM

THE CLASSES ARE :  
 KHONDALITES, UNCLASSIFIED CRYSTALLINE ROCKS,  
 RECENT ALLUVIUM OF B2 & B3 AND B4

NCLASS= 3 NFEAT= 3 NSIG= 24 NPROB= 1

THE SIGNALS IN CLASS 1 ARE :

25.00	126.00	118.00
23.00	120.00	118.00
21.00	120.00	114.00
21.00	120.00	114.00
23.00	120.00	110.00
21.00	120.00	110.00
21.00	120.00	106.00
23.00	120.00	106.00

THE SIGNALS IN CLASS 2 ARE :

42.00	75.00	57.00
40.00	70.00	57.00
44.00	68.00	49.00
40.00	64.00	45.00
42.00	70.00	49.00
42.00	75.00	61.00
40.00	70.00	57.00
42.00	70.00	49.00

THE SIGNALS IN CLASS 3 ARE :

22.00	67.00	59.00
20.00	71.00	59.00
22.00	74.00	67.00
24.00	78.00	71.00
26.00	67.00	59.00
24.00	71.00	63.00
20.00	78.00	59.00
24.00	71.00	63.00

NUMBER OF SIGNALS IN CLASS (1)= 8

NUMBER OF SIGNALS IN CLASS (2)= 8

NUMBER OF SIGNALS IN CLASS (3)= 8

THE MATRIX B IS :

-0.05103	0.22701	0.00352
0.59682	-0.30442	-0.02311
0.25421	0.07742	0.01958

## DECISION VECTORS

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SAMPLE NO.	CLASS	D(1)	D(2)	D(3)	DECISION
1	1	4.37	-4.64	1.27	1
2	1	4.48	-4.43	1.05	1
3	1	5.04	-4.80	0.75	1
4	1	5.04	-4.80	0.75	1
5	1	4.47	-4.37	0.00	1
6	1	5.04	-4.76	0.73	1
7	1	5.03	-4.73	0.70	1
8	1	4.47	-4.34	0.87	1
9	2	-4.39	4.39	1.00	2
10	2	-4.20	4.50	0.70	2
11	2	-5.49	5.56	0.93	2
12	2	-4.66	5.20	0.47	2
13	2	-4.77	4.96	0.82	2
14	2	-4.38	4.36	0.02	2
15	2	-4.20	4.50	0.70	2
16	2	-4.77	4.96	0.82	2
17	3	0.69	1.20	-0.89	2
18	3	1.56	0.40	-0.96	1
19	3	1.22	0.43	-0.66	1
20	3	0.96	0.39	-0.36	1
21	3	-0.45	2.00	-0.55	2
22	3	0.43	1.17	-0.58	2
23	3	2.08	-0.31	-0.78	1
24	3	0.43	1.17	-0.59	2

## CLASSIFIED AS

CLASS	1	2	3
1	8	0	0
2	0	8	0
3	4	4	0

PROBABILITIES = 0.333 0.333 0.333

NO. OF MISCALCULATIONS = 8.

CORRECTLY IDENTIFIED OVERALL = 66.6667%

## PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION

CLASS	1	2	3
1	100.00	0.00	0.00
2	0.00	100.00	0.00
3	50.00	50.00	0.00

Let us consider the response of Khandalites in Band-2. These range from 21-25 very much similar to that of Recent alluvium (20-26) in same band. Also, the grey levels of unclassifieds in Band ~ 4 (45-61) is also similar to those of alluvium of same band (59-71). Coming to the response of alluvium in Band 3, some of them are similar to those of class (2) of same band. Thus, the third class lost its 'identity' during the classification stage. An inference drawn from this is that the bands we choose for various classes should give unique identity to them. This may be achieved with a data of good number of bands. However, it is found later that a combination of two bands gives excellent results for mapping with the classifier.

Next, another class is added to these three and tested as 4-Class, 2-Feature problems. The classes are Khandalites, unclassifieds, Recent alluvium and coastal sandy soil and the features are Band -1 and Band-3 responses. It is worth noting that the classifier give 100 % accurate results in this case also. With the same bands, charnockite as the fifth class, the classifier identified the classes with 72 % accuracy. This may be due to the association of charnockites with unclassifieds. The outputs of these two classifications and co-ordinates of the classes on the imagery are not available for reproduction because of system H/I problems at the last phase of the work.

So, in the next step, charnockites has been dropped and a

surface feature (water bodies) is substituted. The results showed that two of the unclassifieds are identified with sandy soils and the rest with water bodies. Thus, the whole class is misidentified by the classifier (Table 2.5).

#### 2.4.2 Surface Feature Identification

The study area includes many interesting surface features such as rivers, reserve forests, lakes, marshy lands, coconut plantations along the sea coast, built up areas. Location of these features is made with the help of topographical maps of the area. These geographical co-ordinates are converted into image co-ordinates to enable the data retrieval from CCT. Three of these features namely water bodies, built up areas and dense jungles are chosen for the computerised statistical classification. Dense jungles are Muttayyapalem Reserve Forests (RF), Water bodies (Krishna river and Bay of Bengal) built up areas being urban regions of the area. Table 2.6 gives the geographical and image coordinates of these locations.

First, eight samples each of water bodies and built up areas are subjected to classification and the outcome is free of any miscalculations (Table 2.7). Bands used for this are 3 and 4 of MSS. Next, another 2-class, 2-features problem is developed with water bodies and dense jungles as classes and Band-3 and Band-4 values as features. This time also, the results are 100% accurate (Table 2.8).

TABLE 2.5

5-CLASS, 2-FEATURE PROBLEM

THE CLASSES ARE :  
 1) VOLCANITES, UNCLASSIFIED, RECENT ALLUVIUM AND  
 SANDY SOILS , WATER OF B1 & B3

CLASS= 5 NFEAT= 2 NSIG= 40 NPPDB= 1

THE SIGALS IN CLASS 1 ARE :

37.00	126.00
30.00	120.00
31.00	120.00
34.00	120.00
37.00	120.00
34.00	120.00
39.00	120.00
37.00	120.00

THE SIGALS IN CLASS 2 ARE :

49.00	75.00
49.00	70.00
49.00	68.00
44.00	64.00
44.00	70.00
49.00	75.00
49.00	76.00
44.00	70.00

THE SIGALS IN CLASS 3 ARE :

30.00	67.00
32.00	71.00
32.00	74.00
32.00	78.00
34.00	67.00
32.00	71.00
30.00	78.00
30.00	71.00

THE SIGALS IN CLASS 4 ARE :

59.00	104.00
57.00	104.00
49.00	100.00
59.00	93.00
56.00	93.00
70.00	87.00
82.00	97.00
79.00	97.00

THE SIGALS IN CLASS 5 ARE :

55.00	28.00
55.00	34.00
55.00	31.00
59.00	34.00
51.00	30.00
54.00	34.00
46.00	32.00
54.00	36.00

NUMBER OF SIGNALS IN CLASS (1)= 8  
 NUMBER OF SIGNALS IN CLASS (2)= 8  
 NUMBER OF SIGNALS IN CLASS (3)= 8  
 NUMBER OF SIGNALS IN CLASS (4)= 8  
 NUMBER OF SIGNALS IN CLASS (5)= 8

THE MATRIX B IS :

$$\begin{bmatrix} -1.04799 & 0.04057 \\ 0.00216 & -0.00781 \\ -0.09355 & -0.01301 \\ 0.11930 & 0.02968 \\ 0.02008 & -0.04944 \end{bmatrix}$$

CLASSIFIED AS					
CLASS	1	2	3	4	5
1	8	0	0	0	0
2	0	0	0	2	5
3	0	0	8	0	0
4	0	0	0	8	0
5	0	0	0	0	8

PROBABILITIES= 0.200 0.200 0.200 0.200 0.200

NO. OF MISCALCULATIONS = 8.

% CORRECTLY IDENTIFIED OVERALL= 80.00000

#### PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION

CLASS	1	2	3	4	5
1	100.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	25.00	75.00
3	0.00	0.00	100.00	0.00	0.00
4	0.00	0.00	0.00	100.00	0.00
5	0.00	0.00	0.00	0.00	100.00

DECISION BOUNDARIES

32

THE BOUNDARY BETWEEN CLASS 1 AND CLASS 2 IS :

$$-0.01003004 X_1 + 0.00967685 X_2 = 0.29116433$$

THE BOUNDARY BETWEEN CLASS 2 AND CLASS 3 IS :

$$0.01914317 X_1 + 0.00103885 X_2 = 0.96541861$$

THE BOUNDARY BETWEEN CLASS 3 AND CLASS 4 IS :

$$-0.04257096 X_1 + -0.00853766 X_2 = -2.63250240$$

THE BOUNDARY BETWEEN CLASS 4 AND CLASS 5 IS :

$$0.01984330 X_1 + 0.01582383 X_2 = 2.15062320$$

THE BOUNDARY BETWEEN CLASS 5 AND CLASS 1 IS :

$$0.01361453 X_1 + -0.01800186 X_2 = -0.77470373$$

TABLE 2.6

Reflectance Values

S.No.	Feature/Location	Geographical Coordinates						Image Coordinates			Reflectance Values		
		Latitude		Longitude		Scan Line Pixel		B-1	B-2	B-3	B-4		
		D N M S	M S D N	S D M N		S D M N							
<u>Water Bodies</u>													
1.	Krishna near Vizianthagad	16	35	00	80	25	35	211	444	55	52	28	11
2.	-do-	16	35	00	80	26	19	209	467	56	56	34	8
3.	Krishna near Popuru	16	36	05	80	15	44	220	128	60	52	31	7
4.	Krishna near Konuru	16	36	29	80	13	31	218	56	59	58	34	11
5.	Bay off Bengal	16	15	00	81	15	00	484	2130	51	39	20	11
6.	-do-	16	15	00	81	30	00	433	2600	44	28	24	7
7.	-do-	16	15	00	81	45	00	382	3069	46	29	22	11
8.	Gogulleru Creek	16	21	08	81	20	17	332	2252	54	50	36	11
<u>Built up Areas</u>													
1.	Vijayawada	16	31	05	80	36	28	261	811	53	71	86	53
2.	Machilipatnam	16	11	04	81	08	49	591	1965	45	37	82	61
3.	Guntur	16	17	42	80	26	45	586	601	60	68	77	63
4.	Tenali	16	14	03	80	39	42	623	1032	33	24	77	63
5.	Chirala	15	49	43	80	22	03	1214	648	54	58	91	67
6.	Narsapur	16	26	01	81	42	04	151	2899	33	28	70	57
7.	Bhimavaram	16	32	25	81	31	54	46	2535	30	23	88	77
8.	Ongole	15	54	11	80	28	05	1096	807	45	46	92	70

Table 2.6 Continued....

Dense Jungles

1.	Muttayyapalem RF	15	51	45	80	29	34	1144	870	36	39	81	62
2.	-do-	15	51	10	80	29	34	1157	874	36	43	93	87
3.	-do-	15	50	50	80	29	34	1164	877	44	41	110	98
4.	-do-	15	52	18	80	30	44	1128	903	34	27	77	62
5.	-do-	15	52	18	80	31	55	1124	940	43	33	74	59
6.	-do-	15	52	18	80	32	10	1124	948	43	44	87	71
7.	-do-	15	52	18	80	32	45	1122	966	44	33	85	70
8.	-do-	15	52	18	80	33	00	1121	974	42	34	81	63

2-CLASS, 2-FEATURE PROBLEM

THE CLASSES ARE : WATER BODIES AND BUILT-UP AREAS IN BAND=3 & BAND=4

N-CLASSE= 2 NFEAT= 2 NSTG= 16 NPROB= 1

THE SIGNALS IN CLASS 1 ARE :

28.00	11.00
31.00	8.00
31.00	7.00
34.00	11.00
20.00	11.00
24.00	7.00
22.00	11.00
36.00	11.00

THE SIGNALS IN CLASS 2 ARE :

86.00	53.00
82.00	61.00
77.00	63.00
77.00	63.00
91.00	67.00
70.00	57.00
88.00	77.00
86.00	65.00

NUMBER OF SIGNALS IN CLASS (1)= 8

NUMBER OF SIGNALS IN CLASS (2)= 8

THE MATRIX B IS :

-0.01225	-0.02411
.0.01225	0.02411

DECISION VECTORS

SAMPLE NO.	CLASS	D(1)	D(2)	DECISION
1	1	0.97	0.03	1
2	1	0.97	0.03	1
3	1	1.00	0.00	1
4	1	0.94	0.06	1
5	1	1.02	0.02	1
6	1	1.05	0.05	1
7	1	1.01	0.01	1
8	1	0.93	0.07	1
9	2	0.11	0.89	2
10	2	0.04	0.96	2
11	2	0.05	0.95	2
12	2	0.05	0.95	2
13	2	-0.09	1.09	2
14	2	0.16	0.84	2
15	2	-0.19	1.19	2
16	2	-0.03	1.07	2

~~CLASSIFIED AS~~

CLASS	1	2
1	8	0
2	0	8

PROBABILITIES = 0.500 0.500

NO. OF MISCALCULATIONS = 0

PERCENT CORRECTLY IDENTIFIED OVERALL = 100.00000

PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION

CLASS	1	2
1	100.00	0.00
2	0.00	100.00

~~DECISION BOUNDARIES~~

THE BOUNDARY BETWEEN CLASS 1 AND CLASS 2 IS :

$$-0.01225063 X_1 + -0.02411196 X_2 = -1.55695820$$

THE BOUNDARY BETWEEN CLASS 2 AND CLASS 1 IS :

$$0.01225063 X_1 + 0.02411196 X_2 = 1.55695820$$

TABLE 2.8

2-CLASS, 2-FEATURE PROBLEM

THE CLASSES ARE : WATER BODIES AND DENSE JUNGLES OF BAND-3 & BAND-4

NCLASS= 2 NFEAT= 2 NSTG= 16 NPROB= 1

THE SIGNALS IN CLASS 1 ARE :

28.00	11.00
34.00	8.00
31.00	7.00
31.00	11.00
20.00	11.00
24.00	7.00
22.00	11.00
36.00	11.00

THE SIGNALS IN CLASS 2 ARE :

81.00	62.00
93.00	87.00
110.00	98.00
77.00	62.00
74.00	59.00
87.00	71.00
85.00	70.00
81.00	63.00

NUMBER OF SIGNALS IN CLASS (1)= 8

NUMBER OF SIGNALS IN CLASS (2)= 8

THE MATRIX 'D' IS :

-0.01726	-0.01387
0.01726	0.01387

DECISION VECTORS

SAMPLE NO.	CLASS	b(1)	b(2)	DECISION
1	1	0.96	0.04	1
2	1	0.93	0.07	1
3	1	0.96	0.04	1
4	1	0.91	0.09	1
5	1	1.03	-0.03	1
6	1	1.02	-0.02	1
7	1	1.01	-0.01	1
8	1	0.89	0.11	1
9	1	0.16	0.85	2
10	1	0.13	1.17	2
11	2	-0.75	1.35	2
12	2	0.18	0.82	2
13	2	0.23	0.77	2
14	2	0.03	0.37	2
15	2	0.06	0.94	2
16	2	0.11	0.46	2

CLASSIFIED AS:

CLASS	1	2
1	8	0
2	0	8

PROBABILITIES= 0.500 0.500

NO. OF MISCALCULATIONS = 0

PERCENT CORRECTLY IDENTIFIED OVERALL= 100.00000

PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION

CLASS	1	2
1	100.00	0.00
2	0.00	100.00

DECISION BOUNDARIES

THE BOUNDARY BETWEEN CLASS 1 AND CLASS 2 IS :

$$-0.01725602 X_1 + -0.01387335 X_2 = -1.55172370$$

THE BOUNDARY BETWEEN CLASS 2 AND CLASS 1 IS :

$$0.01725602 X_1 + 0.01387335 X_2 = 1.55172370$$

Having known that the classifier is able to classify two classes at a time successfully, now, all the three (water bodies, built up areas and dense jungles in order) of bands 3 and 4 are tried. After classification, it is found that four of the built up area samples are identified with dense jungles while two of the latter class are identified with built up area class. The percent correctly identified overall is 75.0 % (Table 2.9). To improve this percentage, the combination of Band-2 and Band -3 signals is tried (Table 2.10). This time, all the eight signals of the third class are correctly identified while three of built up class are recognised with third class. The percentage of correct identification, thus, becomes 87.5 %, a marked 12.5 % increase over the previous combination. Other combinations may also be tried to see whether it still can be improved.

Finally, a 3 class- 3 feature problem is developed with the some classes of bands 2, 3 and 4 signals (Table 2.11). The percentage of correct identification, expectedly, fell down to 54.16 %. The confusion matrix shows that three of the first class samples associated with the second one and the second class samples totally misrepresented.

#### 2.4.3 Mapping with the Classifier

Now that we are sure that the classifier gives more than satisfactory results with a combination of 2 bands, a small region

TABLE 2.9

3-CLASS, 2-FEATURE PROBLEM

THE CLASSES ARE :  
 WATER BODIES, BUILT-UP AREAS AND DENSE JUNGLES OF BAND-3 &  
 BAND-4

NCLASS= 3 NFEAT= 2 NSIG= 24 NPROBE= 1

THE SIGNALS IN CLASS 1 ARE :

28.00	11.00
34.00	8.00
31.00	7.00
34.00	11.00
20.00	11.00
24.00	7.00
22.00	11.00
36.00	11.00

THE SIGNALS IN CLASS 2 ARE :

86.00	53.00
82.00	61.00
77.00	63.00
77.00	63.00
91.00	67.00
70.00	57.00
88.00	71.00
86.00	65.00

THE SIGNALS IN CLASS 3 ARE :

81.00	62.00
93.00	87.00
110.00	98.00
77.00	62.00
74.00	59.00
87.00	71.00
85.00	70.00
81.00	63.00

NUMBER OF SIGNALS IN CLASS (1)= 8

NUMBER OF SIGNALS IN CLASS (2)= 8

NUMBER OF SIGNALS IN CLASS (3)= 8

THE MATRIX B IS :

-0.03354	-0.01546
0.07374	-0.05031
-0.04020	0.06577

## DECISION VECTORS

SAMPLE NO.	CLASS	D(1)	D(2)	D(3)	DECISION
1	1	0.94	0.03	0.02	1
2	1	0.89	0.23	0.12	1
3	1	0.53	0.17	0.10	1
4	1	0.88	0.18	0.05	1
5	1	1.03	0.16	0.13	1
6	1	0.01	0.00	0.01	1
7	1	1.01	0.12	0.10	1
8	1	0.86	0.23	0.08	1
9	2	0.08	0.52	0.17	2
10	2	0.13	0.36	0.51	2
11	2	0.05	0.36	0.41	2
12	2	0.24	0.29	0.47	2
13	2	0.07	0.55	0.67	2
14	2	0.02	0.55	0.43	2
15	2	0.09	0.48	0.43	2
16	2	0.17	0.36	0.82	2
17	2	0.42	0.59	0.83	2
18	3	0.13	0.38	0.48	3
19	3	0.18	0.36	0.46	3
20	3	0.02	0.48	0.50	3
21	3	0.00	0.44	0.55	3
22	3	0.08	0.46	0.45	3
23					
24					

## CLASSIFIED AS

CLASS	1	2	3
1	8	0	0
2	0	4	(4)
3	0	(2)	6

PROBABILITIES = 0.333 0.333 0.333

NO. OF MISCALCULATIONS = 6.

CORRECTLY IDENTIFIED OVERALL = 75.00000 %

## PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION

CLASS	1	2	3
1	100.00	0.00	0.00
2	0.00	50.00	50.00
3	0.00	25.00	75.00

DECTSTON BOUNDARIES  
-----

THE BOUNDARY BETWEEN CLASS 1 AND CLASS 2 IS :

$$-0.03575919 X_1 + 0.01161466 X_2 = -1.78625150$$

THE BOUNDARY BETWEEN CLASS 2 AND CLASS 3 IS :

$$0.05795267 X_1 + -0.03865066 X_2 = 0.62900282$$

THE BOUNDARY BETWEEN CLASSES 3 AND CLASSES 1 IS :

$$-0.00222208 X_1 + 0.02707600 X_2 = 1.15724870$$

TABLE 2.10

3-CLASS, 2-FEAT PROBLEM

THE CLASSES ARE :  
WATER BODIES, BUILT-UP AREAS AND DENSE JUNGLES OF BAND=2 & BAND=3

NCLASS= 3 NFEAT= 2 NSTG= 24 NPROB= 1

THE SIGNALS IN CLASS 1 ARE :

52.00	28.00
56.00	34.00
52.00	31.00
58.00	34.00
39.00	20.00
28.00	24.00
29.00	22.00
50.00	36.00

THE SIGNALS IN CLASS 2 ARE :

71.00	86.00
37.00	82.00
58.00	77.00
24.00	77.00
58.00	91.00
28.00	70.00
47.00	86.00
46.00	92.00

THE SIGNALS IN CLASS 3 ARE :

39.00	81.00
43.00	93.00
41.00	110.00
27.00	77.00
33.00	74.00
44.00	87.00
33.00	85.00
34.00	81.00

NUMBER OF SIGNALS IN CLASS (1)= 8

NUMBER OF SIGNALS IN CLASS (2)= 8

NUMBER OF SIGNALS IN CLASS (3)= 8

THE MATRIX R IS :

0.01371	-0.04907
0.02599	0.02237
-0.03973	0.02670

## DECISION VECTORS

SAMPLE NO.	CLASS	D(1)	D(2)	D(3)	DECISION
1	1	0.99	0.13	-0.12	1
2	1	0.91	0.21	-0.12	1
3	1	0.93	0.15	-0.09	1
4	1	0.92	0.22	-0.14	1
5	1	1.06	0.04	-0.02	1
6	1	0.95	0.11	-0.15	1
7	1	0.98	0.12	-0.13	1
8	1	0.85	0.13	-0.15	1
9	2	0.13	0.73	0.56	2
10	2	0.04	0.40	0.11	2
11	2	0.26	0.63	0.69	2
12	2	0.06	0.25	0.35	2
13	2	-0.01	0.65	0.57	2
14	2	0.19	0.23	0.46	2
15	2	0.02	0.52	0.45	2
16	2	-0.08	0.41	0.52	2
17	2	-0.06	0.53	0.58	2
18	3	-0.11	0.64	0.75	3
19	3	-0.40			3
20	3	0.08	0.28	0.65	3
21	3	0.15	0.31	0.54	3
22	3	-0.01	0.50	0.51	3
23	3	-0.03	0.39	0.56	3
24	3	0.04	0.37	0.59	3

## CLASSIFIED AS

CLASS	1	2	3
1	8	0	0
2	0	5	3
3	0	0	8

PROBABILITIES = 0.333 0.333 0.333

NO. OF MISCALCULATIONS = 3.

CORRECTLY IDENTIFIED OVERALL = 87,50000

## PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION

CLASS	1	2	3
1	100.00	0.00	0.00
2	0.00	62.50	37.50
3	0.00	0.00	100.00

DECISION BOUNDARIES

THE BOUNDARY BETWEEN CLASS 1 AND CLASS 2 IS :

$$-0.00409157 X_1 + -0.02381191 X_2 \approx -1.74242260$$

THE BOUNDARY BETWEEN CLASS 2 AND CLASS 3 IS :

$$0.02189378 X_1 + -0.00144339 X_2 \approx 0.85109085$$

THE BOUNDARY BETWEEN CLASS 3 AND CLASS 1 IS :

$$-0.01780222 X_1 + 0.02525530 X_2 \approx 0.89133170$$

TABLE 2.11

3-CLASS, 3-FEATURE PROBLEM

THE CLASSES ARE :  
WATER BODIES, BUILT-UP AREAS, AND DENSE JUNGLES IN B=2, B=3, & B=4

NCLASS= 3 NFEAT= 3 NSTG= 24 NPROB= 1

THE SIGNALS IN CLASS 1 ARE :

52.00	28.00	11.00
56.00	34.00	8.00
52.00	31.00	7.00
58.00	34.00	11.00
39.00	20.00	11.00
28.00	24.00	7.00
29.00	22.00	11.00
50.00	36.00	11.00

THE SIGNALS IN CLASS 2 ARE :

71.00	86.00	53.00
37.00	82.00	61.00
68.00	77.00	58.00
24.00	77.00	63.00
58.00	91.00	67.00
28.00	70.00	57.00
47.00	86.00	65.00
46.00	92.00	70.00

THE SIGNALS IN CLASS 3 ARE :

39.00	81.00	62.00
43.00	93.00	87.00
11.00	110.00	98.00
27.00	77.00	62.00
33.00	74.00	59.00
44.00	87.00	71.00
33.00	85.00	70.00
34.00	81.00	63.00

NUMBER OF SIGNALS IN CLASS (1)= 8

NUMBER OF SIGNALS IN CLASS (2)= 8

NUMBER OF SIGNALS IN CLASS (3)= 8

THE MATRIX B IS :

0.62630	-0.09400	0.00720
-0.27698	0.03517	-0.08067
-0.01940	0.05883	0.07348

## DECISION VECTORS

SAMPLE NO.	CLASS	D(1)	D(2)	D(3)	DECISION
1	1	3.26	0.06	-2.03	1
2	1	3.90	-0.15	-2.75	1
3	1	3.16	-0.21	-2.37	1
4	1	4.33	-0.42	-2.51	1
5	1	0.80	-1.17	-0.97	1
6	1	-1.63	-2.34	-0.29	1
7	1	-1.35	-2.12	-0.23	1
8	1	2.60	-0.34	-1.94	1
9	1	5.51	-2.14	-2.37	1
10	2	-5.44	-0.74	-1.70	1
11	2	-5.18	-2.10	-2.08	1
12	2	-3.99	-1.83	-3.17	1
13	2	-2.68	-1.26	-0.42	1
14	2	-2.95	-1.54	-0.42	1
15	2	0.53	-0.25	-0.71	1
16	2	0.15	-0.22	-0.57	1
17	2	-0.99	-0.51	-1.47	1
18	3	-0.47	-0.39	-0.66	1
19	3	-1.39	-0.30	-2.69	3
20	3	-3.37	1.58	2.79	3
21	3	-2.03	1.07	1.95	3
22	3	-0.11	-0.12	-1.25	3
23	3	-2.35	0.90	2.45	3
24	3	-2.03	0.95	2.08	3

## CLASSIFIED AS

CLASS	1	2	3
1	5	3	0
2	3	0	5
3	0	0	8

PROBABILITIES = 0.333 0.333 0.333

NO. OF MISCALCULATIONS = 11

PERCENT CORRECTLY IDENTIFIED OVERALL = 54.16667

## PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION

CLASS	1	2	3
1	62.50	37.50	0.00
2	37.50	0.00	62.50
3	0.00	0.00	100.00

of the study area is chosen to generate a computer map based on K-Class Classifier decisions. The coordinates of the area are shown in figure 2.3.

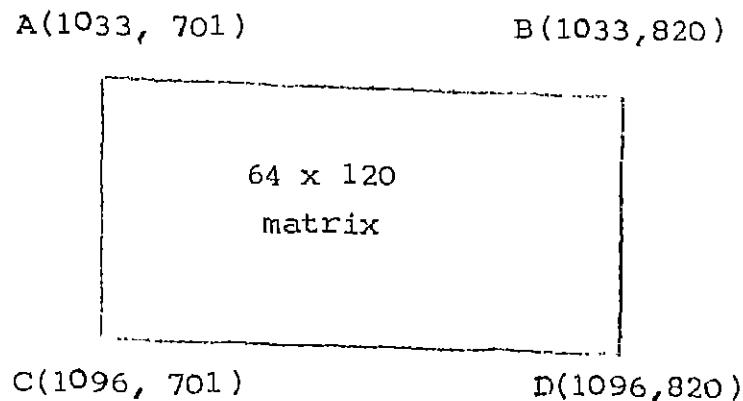


Fig. : 2.3

From the toposheet, it is observed that there are only two classes present in the area viz water and non-water area. The criterion for the selection of this region is that in this small region, Kommamur Canal and Nallamara Vagu intersect each other. Also, a reservoir is present near the end D. The digital data of Band-2 and Band-3 of this area is retrieved for the analysis. The 64 x 120 data matrix is assumed to contain two classes and the computer map is generated (Fig. 2.4).

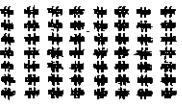
It is worth noting the date of satellite pass for the data obtained (28th September 1983). This period is a harvest period

2. Water Bodies

1. Agriculture



Legend



and the crop is generally paddy. So, the classes actually identified are agriculture and water bodies. The number of pixels present in each class is given below the map.

Now, some more lines of data preceding this area are added to this making the co-ordinates of A and B as A(1001, 701), B(1001, 701). This is done because this added area contains a village namely Return. The map generated by the classifier beautifully shows this village (Fig. 2.5). Another feature uncovered in toposheets is also observed on the map. This being a regular (hallow, square-like) feature this is to be taken as a man-made feature. This is identified as water body but it may be deducted from its dimensions as a foundation trench filled with water. Number of pixels present in each class and area occupied by it in percentage is given as its annotation.

The software developed for this work is explained under the head SOFTWARE in Appendix - 2. The listings appear in subsequent appendices.

**RESERVOIR**

**RETUR VILLAGE**

Retur village is located in the northern part of the map. It is bounded by the Nommamur Canal to the west and the Tungabhadra River to the east. The village is situated on a plateau with several small hills. The terrain is relatively flat, with some minor fluctuations in elevation. The village itself is a cluster of houses and agricultural plots.

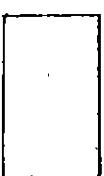
**LAMARKA VAGU**

Lamarka Vagu is a small stream or watercourse that flows through the central part of the map. It originates from a small hill on the western side and flows generally eastward, eventually joining the Tungabhadra River. The stream is characterized by its narrow, rocky bed and turbulent flow.

**NOMMAMUR CANAL**

The Nommamur Canal is a major irrigation canal that runs through the southern part of the map. It originates from the Tungabhadra River and flows generally westward, eventually emptying into the same river. The canal is wide and deep, with a smooth, paved surface. It is flanked by a series of embankments and drainage ditches.

**Legend**



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1. Agriculture

CLASS (1)  
9738

2. Water bodies

CLASS(2)  
1522



3. Built-up

CLASS(3)  
240

#### 2.4.4 Observation and Conclusions

The classifier with 2-class and 2-band problem gave almost 100 % correct identification. With 3-band signals of MSS, the percentage accuracy drastically falls down. The classifier gave 100 % accurate results in identifying Khondalities, Recent alluvium, Coastal Sandy and unclassified soils. Infact, it can be deducted what exactly unclassifieds are with different trials with the classifier.

Coming to the classification of surface features, 2-band, 2-class cases gave satisfactory results whereas while classifying waterbodies, built up areas and dense jungles with Bands 3 & 4 signals, it dropped down to 75 %. This is improved by 12.5 % with Band-2 and Band-3 signals.

The line printer map showing the three classes viz. agriculture, water bodies and built-up area prepared on the basis of classifier decisions matches with the topo sheet details. It, infact, showed some more details.

CHAPTER - III  
VISUAL INTERPRETATION OF MSS IMAGERY

3.1 Introduction

Though quite young, the field of aerial photography developed a number of broad divisions, each in itself having a remarkable diversity. Of its many offshoots, aerial photo-interpretation has acquired prominence because of its effectiveness of the technique. The technique includes the characteristics like identification of man-made features, common terrain features, feature analysis, use of stereoscope etc. Though being an effective method, it is costly in view of the flights, man-hours and sophisticated equipment that be used in the process to get the photographs. Now that, many satellites are operational and their products available at reasonable prices to the users round the world, visual interpretation of satellite imagery acquires a new-found significance.

3.2 Elements of Photo Interpretation for Terrain Evaluation

As it is not proper to call an imagery interpretation as photo interpretation, a new term visual interpretation of satellite imagery (VISI) is coined for subsequent use.

The visual interpretation of imagery for terrain evaluation is based on the spectral response of the ground objects. The key elements for the evaluation and interpretation are listed below.

- a) Topography or landform
- b) Surface drainage pattern
- c) Spectral responses or gray levels
- d) Vegetation and Landuse

All the above elements are studied sequentially using imageries of Bands 1, 2 and 4 of Landsat-4.

### 3.2.1 Landform:

Landform, in its broadest sense, implies the shape of the land i.e. topography. Each landform and bed rock type has its own characteristic topographic form, including a typical size and shape. In fact, there is often a distinct topographic change at the boundary between two different landforms. It is well known that once the origin rocktype-landform of a given area has been established, a large proportion of the interpretation is complete and the remainder will follow with comparative ease. The first part of the composite noun i.e. origin includes igneous, sedimentary and metamorphic and other fluvial origins.

Under each of the primary origins applicable to rocks (igneous, sedimentary and metamorphic) there are numerous different materials. These materials differ in many aspects: texture, mineralogical composition, nature of original source, secondary origin, etc. Based on these characteristics, these materials may be classified into families or 'rock types'. The features such

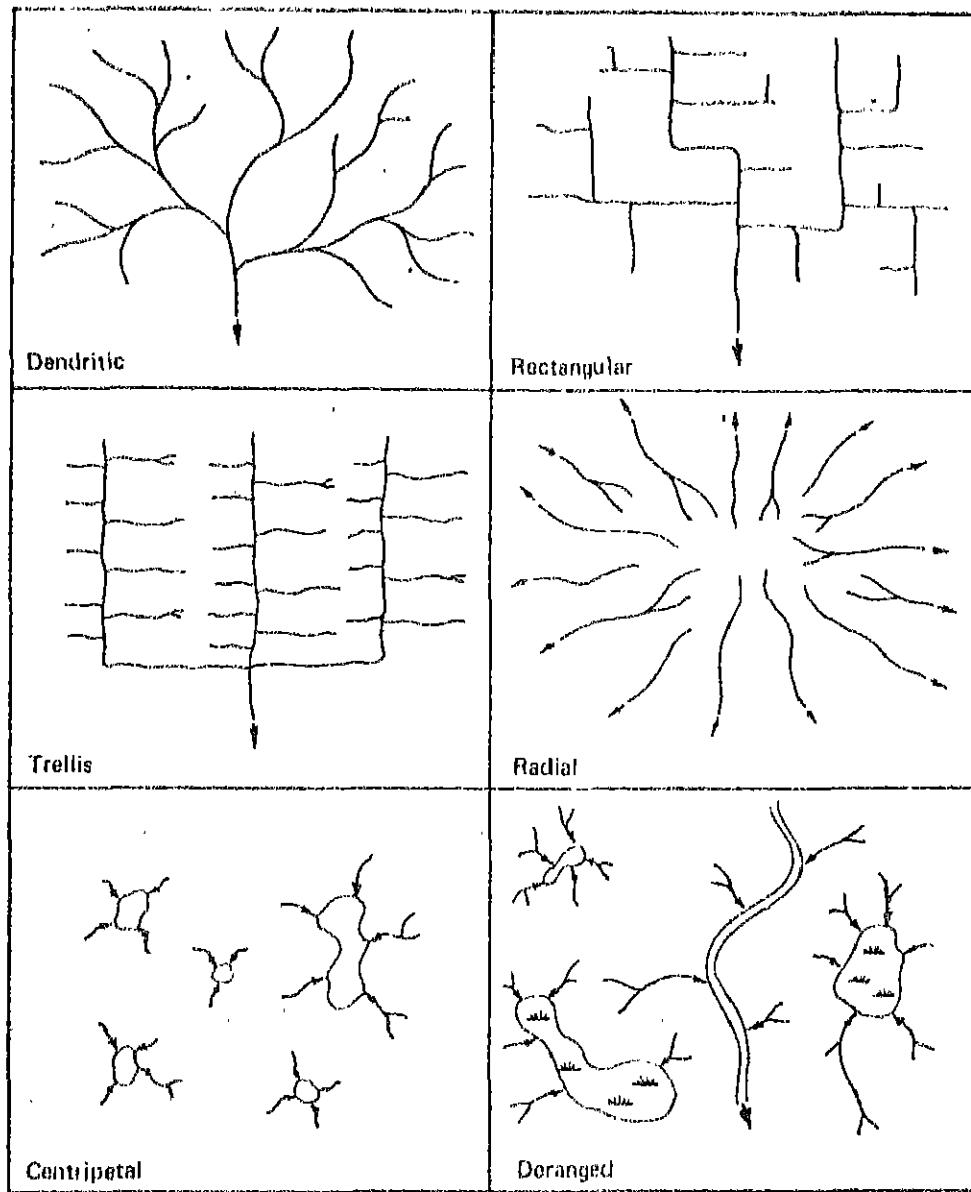
as hills can be identified by their suggestive shapes.

### 3.2.2 Drainage Pattern

The drainage pattern and texture seen on any imagery are indicators of landform and bedrock type and also suggest soil characteristics and site drainage conditions. Six of the most common drainage patterns are illustrated in Figure 3.1.

The dendritic drainage pattern is a well integrated pattern formed by main stream with its tributaries branching and rebranching freely in all directions and occurs on relatively homogeneous materials. The rectangular drainage pattern is basically a dendritic pattern modified by structural bed rock control such that the tributaries meet at right angles. The trellis pattern consists of streams having one dominant direction and tributaries at right angles. The radial pattern is formed by streams that radiate outward from a central area as is typical of volcanoes and domes. The centripetal pattern is the reverse of radial drainage pattern. The deranged drainage pattern is a disordered pattern of aimlessly directed short streams, ponds, and wetland areas typical of ablation glacial till areas.

Based on drainage texture, they are broadly divided as coarse textured and fine textured drainage patterns. The former develop where the soils and rocks have good internal drainage with little surface run off. It is reverse with the latter pattern and observed on easily eroded rocks such as shale.



**Figure 3.4** Six basic drainage patterns.

### 3.2.3 Spectral Responses

The spectral response refers to the 'tone' or 'brightness' at any point on the imagery. As the satellites have sensors with wide ranging wavelengths, interpretation of the surface features becomes very easy. For example, the water bodies will be darkest in tone (around 8-15 in grey level) in Band -4 imagery. But they can be better mapped from Band-2 imagery where they appear somewhat lighter in tone against a darker background. Thus, varying spectral responses for various wavelengths can be made use of in visual interpretation. False coloured composites and Thermal IR imagery may help identify some more features. The interpreter has to develop his own keys while dealing with these wide ranging products.

### 3.2.4 Vegetation and Land Use

For identifying various vegetation types and changes the colour-IR film is proved to be the best one. With MSS imagery this process becomes almost impossible. Only vegetation cover we can detect is on hill tops. This identification is easy because of the peculiar dark tone of the cover amidst its lighter surroundings. While searching for this element of interpretation, One should be knowledgeable about its changes through the year and accordingly he should evolve keys. During the crop period, the true tonal patterns of soils are 'hidden' as only the crop is responsive to spectral analysis.

### 3.3 Identification of Rock Types

An effort is made to identify the various rock types present in the area under study. After thorough VISI of the three band imageries (Bands 1, 2, and 4 of Landsat ~4), it is concluded that the area primarily consists of two types of rocks viz. sedimentary and igneous. Again in sedimentary type, the consolidated and unconsolidated regions are clearly demarcated using B-2 imagery. The boundaries separating these rock types are drawn with exact precision. But, the bedding, jointing etc. are not prominent as the scale of the imagery is too large.

We first consider the characteristics of that helped identify the sandstone and other types latter.

#### 3.3.1 Sandstone

Topography : massive, seemingly flat topped

Drainage : no drainage. The area is very small and seemingly uninhabited. No gullies because of excellent interval drainage

Spectral response : Light toned because of high quartz content.

As it is surrounded by darker Recent Alluvium it can be mapped from both Band-1 and Band-2 imagery.

Vegetation and Land Use: Sparse vegetation, Land use is rare.

To confirm the above decision, a field test will do but

is not necessitated as the Geological Survey of India maps furnish all such details.

### 3.3.2 Recent Alluvium (Deltas)

Deltas form where streams discharge into bodies of quiet water. The delta area surrounding Krishna and Godavary areas is distinctively seen on Band-2 imagery. This region is extremely flat interrupted only by irregularities associated with distributaries. Surface-drainage patterns in this area are constructional i.e. the drainage patterns whose development has been modified in a pronounced way by the operation of depositional-geologic processes. Because of the huge sediments carried by these rivers, the region has become very fertile and most productive.

#### 3.3.2.1 VISI of Deltas

Topography : Nearly level surface bounded by upland areas and Water Krishna delta has modified arcuate shape,

Drainage and Erosion: Distributary streams present. The delta has many major channels arranged in a fan-shaped pattern. Krishna River and other distributory channels are typically braided.

Photo Tone: The soil is moist because of the shallow water depths (0.5 m to 5 m). Hence low reflectance values (20 to 30 in Band-2) are observed in the region.

Vegetation and Landuse : Extensively used for agriculture. The rock type in this region is identified as Recent Alluvium (Sedimentary - unconsolidated) of fluvial origin.

### 3.3.3 Salinity Survey

The areas where high salt concentrations (saline or alkaline) are present, can be mapped with the help of MSS imagery. The surface expression such as white encrustation will help interpret a part of saline area. In these places, crop vegetation may be extremely sparse or non-existent or may be composed largely of halophytic plants.

Determination of chemical composition and pH values of salt-impregnated areas is the work of field tests.

White encrustations is clearly seen on Band-2 imagery and to some extent on Band-4 imagery. The increase or decrease in salinity may be measured from imageries obtained periodically.

### 3.3.4 Study of River Geometrics

The courses of major streams are displayed in unparalleled clarity and detail on satellite imagery of Band-2. Every curve, channel, distributary is apparent. So, to study the horizontal geometrics of a river, it is simply obtaining the landscapes in which the river of desired course is sensed and arranging them as mosaic.

A frequent problem in unmapped areas, usually remote or relatively inaccessible, is the determination of an approximate stream profile. Satellite pictures provide, in such cases, a means of analysis to study the horizontal geometrics of the stream under steady.

### 3.3.5 Study of Surface Drainage

In many cases, the most carefully prepared and large-scale topographic maps seldom show the tertiary and rill and gully drainage ways. Yet, these very unmapped drainage ways often cause much of the trouble for small development projects,. Also, it is those drainage channels that actually define the extent of any watershed, large or small. Consequently, their omission may be considered a serious flaw in many maps.

Mapping the surface drainage net in all its detail from satellite imageries is easy, quick, reliable and economical. Against the darker background of sedimentary unconsolidated rocks, the water bodies' appearance is distinct. Either paper prints or a black and white film positive may be used for tracing them. Nagaraju (1986) made an attempt to plot them. But as that map does not contain all details like tertiaries, it is revised and presented as Figure 3.2.

### 3.6 Identification of Unclassified Rocks in the Study Area

The Band-2 imagery of the study area, as observed earlier, is excellent for soil as well as surface feature interpretation. Regarding the identification of sedimentary rocks (consolidated and unconsolidated), no serious effort may be made. But the rest of the area, identified as unclassified crystalline rocks by G.S.I. presents a complex picture. It varies in tone unlike alluvial zone. This region consists hills, ponds and other features which are not there in the alluvial zone. This zone, as per GSI, consists both Igneous and Metamorphic rocks which appears in light tone.

Charnockite, that is present adjacent to alluvial zone, is not distinguishable from the available three imageries. This may be due to its some common composition with its neighbourhood.

This zone is shown white in the Figure 3.3

### 3.7 Mapping of Built-Up Area

For mapping of the built-up area in deltaic region, first, one or two prominent towns are located on the image with the help of topo sheets. Their tone is grey and that of surroundings is dark. The towns and villages in this deltaic region appear as patches to specks depending on the extent of their coverage. This grey tone of built-up areas in deltaic zone is somewhat uniformly maintained.

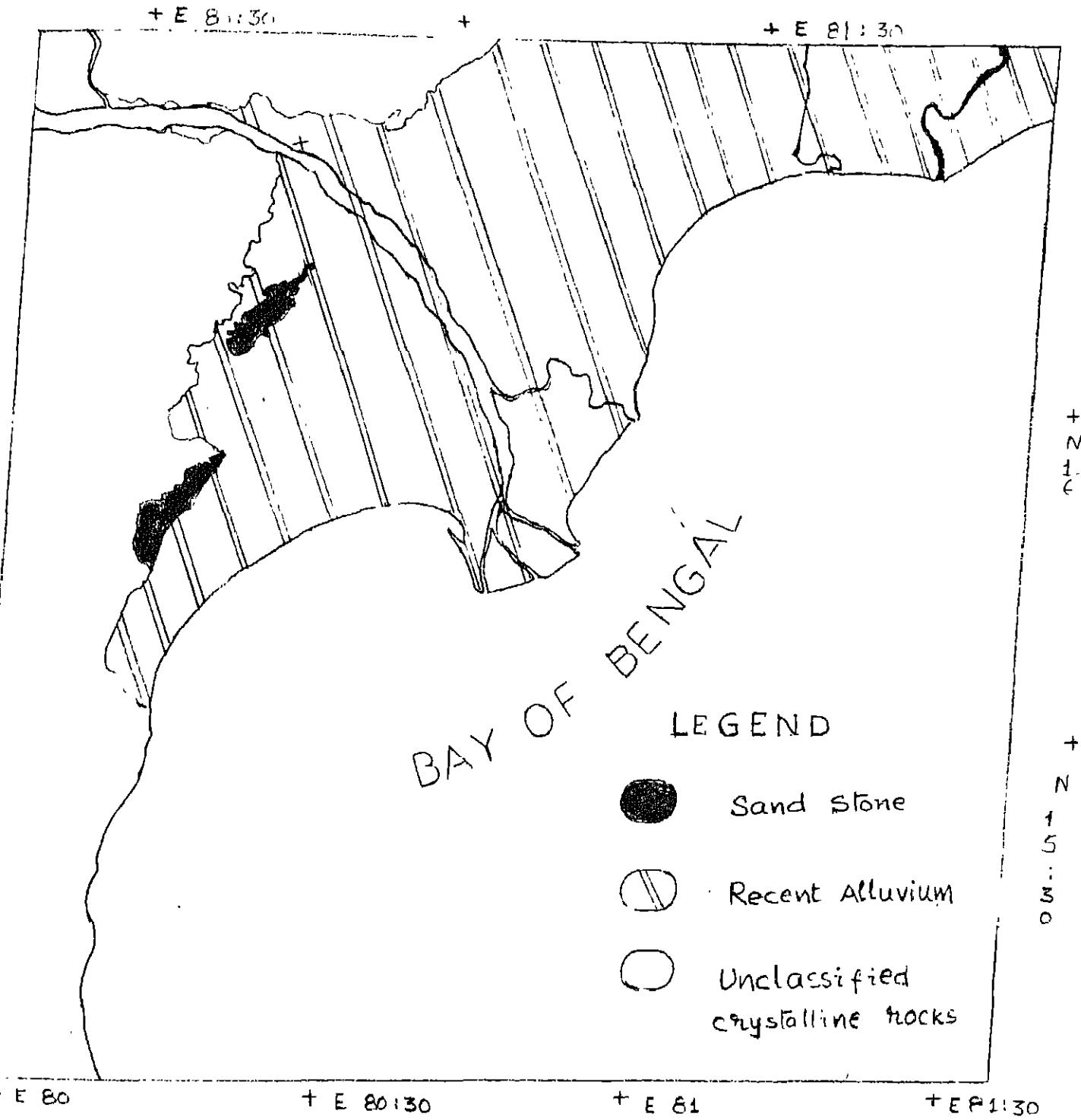


FIG MAP OF ROCK-TYPES

Mapping of this feature from unclassified crystalline rocks (mainly Gneisses) is extremely difficult. They are no longer conspicuous by their tone as the surroundings also more or less maintain the same tone. So, mapping from this rocktype is left out. Figure 3.4 shows the map of built up areas with some prominent towns and cities identified.

### 3.8 Linears

Any linear feature in the landscape which possesses an abnormal degree of regularity is believed to be the surface expression of some structural feature in the bedrock.

Linears may represent one of several structural features; faulting, bedding, jointing, schistosity, gneissosity, contacts or narrow dikes. To identify a linear as one of these features, additional information from other sources is required. Hence, they remain as unidentified linears.

The amount of detail which is desirable in plotting linears is a matter of experience and judgement. The chief trends and character of the linear pattern as shown on "ROSE DIAGRAM" (Fig. 3.6) must be shown as well as its relative density. In the initial phase of interpretation, or for a beginner, it is probably better to err on the side of too much detail; the pattern can always be thinned out at the final interpretation if it tends to obscure other information. The map showing the linears is

labelled Figure 3.5. The linear features shown as broken lines along the shore line are may be due to sea transgression.

### 3.9 Observations and Conclusions

To sum up the salient points noted during the visual interpretation of satellite MSS imagery -

- a) Against the backdrop of alluvial soil, mapping of built up areas, both rural and urban, is very effective and exact from Band-2 image.
- b) Sediment dispersion at river mouths can also be studied from Band-2 but Band-1 picture presents it in a better way. Band-4 picture does not show any sediment discharge at river mouths because of the complete absorption (grey level falls down to a bare minimum of 4 ) of the near -IR electro magnetic energy.
- c) Locating the marshy land around the Kolleru Lake and its correct boundaries is not possible from Band-2 imagery, the reason being both the marshy land and the surrounding alluvial soil appear dark in it. For this purpose, Band-4 picture is used.
- d) Locating small villages situated near the coast is difficult rather it is not possible, as they are situated amidst forests and crooks.

- e) The hillocks can be traced better from Band-4 picture than those of Band 1 and 2. In band-4, their tone is light and are conspicuous by their shape and size.
- f) Surface water features are mapped with remarkable ease in deltaic region from Band-2 imagery.

## CHAPTER 4

### FUTURE RECOMMENDATIONS

With the whole range of satellite products, it is certain that VISI becomes very effective. Other features like vegetation that are not traced in this work will definitely be identifiable in false color composites where two or more bands are mixed to bring out some hidden features.

Band .. 1 picture of Landsat .4 may be used to map the vegetation with the help of Additive Color Viewer (ADDCOL). This requires 70 mm square positive films and the system. It is not carried out as both are not available with the Institute.

The products of high resolution satellites may yield better results. For example, the SPOT simulator data contain a greater range of grey-level values for all water areas than do the Landsat MSS data. The greater spartial resolution of the SPOT simulator data provides informations about small-scale hydrodynamics not available on Landsat MSS data. SPOT simulator data are found to delineate water masses with a high degree of seperation ~~AB~~ (STEVEN et al, 1985). The SPOT data are proved much useful for agriculture, evaluation of geological alterations, forest cover.

With SPOT or Thematic mapper data, the K-Class Classifier results may be highly reliable because of high degree of resolution <sup>map</sup>. It may be interesting to watch how the classifier reacts with) two

bands as input signals.

A soil classification map showing all the three classes of the study area may be prepared with the help of classifier. The area near Guntur where all the three present may be chosen for the purpose. Similarly, Using the classifier, urban areas and their growth can be mapped. Another important application may be flood mapping. In fact, for flood mapping and snow-cover mapping and a simpler method called Density Slicing may be employed.

As the ground water table depths of the study area are available with the Department, it can be <sup>seen</sup> with the help of classifier how many classes are present and also a computer map showing these divisions can be prepared.

The results of this classifier may be compared with those of other classifiers such as Bayes' Classifier.

REFERENCES

1. "A Text Book of Photogrammetry" by Rampal K.K., 1985  
Oxford & IBH Publishers.
2. "Aerial Photographic Interpretation Principles and Applications"  
by Donald R. Lueder, 1959, McGraw Hill Publications.
3. Deekshatalu B.L. and Krishnan R., 1984, "Basic Research Problems in Remote Sensing", Remote Sensing Ed. by Deekshatalu and Rajan.
4. Deekshatalu B.L. and Kamat D.S., 1984. "Data Processing in Remote Sensing", Remote Sensing Ed. by Deekshatalu and Rajan.
5. Fu K.S. 1984, "Pattern Recognition Techniques in Remote Sensing Data Analysis", Remote Sensing Ed. by Deekshatalu and Rajan.
6. Karale, Bali & Rao, 1984., "Soil Mapping Using Remote Sensing Techniques", Remote Sensing Ed. by Deekshatalu and Rajan.
7. Madhavan Unni N.V. 1984, "Forest Survey and Management Using Remote Sensing", Remote Sensing Ed. by Deekshatalu and Rajan.
8. Murthy, Venkataratnam and Saxena, 1984. "Applications of Remote Sensing Techniques for Land Evaluation and Classification for Agriculture", Remote Sensing Ed. by Deekshatalu and Rajan.
9. Nagaraju G.D. Ch. 1986. "Determination of Surface Water Bodics and Ground Water Table Depth Using Remote Sensing", M. Tech. Thesis, I.I.T. Kanpur.

10. Ramamoorthy A.S., 1983. "Snow-melt Run-off Studies Using Remote Sensed Data", Remote Sensing Ed. by Deekshatalu and Rajan.
11. Rampal K.K. 1984 "Determination of Water Table Depths Using Remote Sensed Imagery" I.I.T. Project No. ISRO/CE/KKR/79 .81/3.
12. "Remote Sensing" Edited by Deekshatalu and Rajan, Indian Academy of Sciences, Bangalore, 1984.
13. "Remote Sensing and Image Interpretation" by Thomas M. Lillesand and Ralph W. Kiefer, 1979, John Wiley and Sons, New York.
14. Sashi Kumar M.N., 1982. "Cluster Analysis of Water Table and Reflectance Data Using K-Class Classifier", M.Tech. Thesis, I.I.T. Kanpur.
15. Serreyn D.V. and Nelson G.D., 1973. "The K-Class Classifier", SDSU, RSI Interim Technical Report, RSI-73 .08.
16. Steven G. Ackleson et.al 1985. "A Comparison of SPOT Simulator Data with Landsat MSS Imagery for Delineating Water Masses in Delaware Bars, Broadkill River and Adjacent Wetlands", ASP, Vol. 51, No. 8 pp 1123-1129.

## Commands for a model CHANGE program

```
) ASS MTA1GG
) R CHANGE
) MAKE
) RETAIN
) DSK:*.*=MTA0:t.*//REC:1123/DIM:1600/BDK:10/MODE:EBCDIC/NO ERROR/NOCRLF
```

## HELP CHANGE TEXT

### Commands:

DATA	Specify the name of the data file to be used as in a normal command string "DATA=DEV:FILE.EXE[P,PN]."
MAKE	Call TABLE.SAV to create the conversion tables.
EXIT	Terminate the program.
HELP	This little message.
BYE	Call LOGOUT into core and execute it.
RETAIN	Allows the user to accumulate commands.
RUN	Perform the current command string.
ERASE	Erase retained commands.
PRINT	Print the current command string.

### Switches:

Buffers:x	Use x buffers.
Advance:x	Advance x files before operation.
Backspace:x	Backspace the tape x files before operation.
Block:x	Set blocking factor to x.
Record:x	Set record size or size of largest block to x.
Density:arg	Set mag-tape density to arg [arg=200,556,800].
Retain	Retain the following commands.
Run	Perform the current command and retain it.
Help	These few hints.
Label:arg	Set label type as described below for mag-tape.
Mode:arg	Set file character set as described below.
Parity:arg	Set mag-tape parity [odd=odd, even=even, default=odd].
Password:arg	Set the password for GE labels.
Reel:x	Set serial number in labels that have this feature.
Industry	Initialize for industry compatible 9-channel tape.
Scan	Scan tape for file named.
Error	Don't ignore checksum and parity errors.
Span	Records cross blocks [implied if "/block:0"].
Rewind:arg	Rewind tapes [arg=before, after, always, omit]
Unload	Unload tape after operation.
Tell	Type file names on a wild card search.
List	List the device directory.
Flist	List the device directory [file names only].
Header	Print headers on the line printer.
Crlf	Ascii file has crlf's.

Note: To turn a switch off concatenate "no" with the switch.  
Switches flagged with an (\*) have this feature.

### Label - switch modifiers:

None	Mag-tape has no labels just data [default].
Line	Special labels for DECSYSTEM-10.
Digital	Process labels as standard DIGITAL labels.
Burroughs	Process labels as standard BURROUGHS labels.
IBM	Process labels as standard IBM labels.
GE635	Process labels as standard GE-635 labels.

## Change Text contd..

Note: Labels are written in the mode specified except for IBM and GE-635 labels. IBM labels are written in BCD for 7-track drives and EBCDIC for 9-track drives. GE-635 labels are always written in GE-BCD.

### 'Mode' - switch modifiers:

ASCII	File character set is 7-bit ASCII.
IPASCI	File character set is 8-bit ASCII.
SEASCII	File character set is 9-bit ASCII.
IMAGE	File is read and written as 36-bit words.
SIXBIT	File character set is SIXBIT.
FIXSIX	File character set is SIXBIT with no control words.
ACL	File character set is ACL.
BCD	File character set is BCD.
GEBCD	File character set is GE-BCD.
HONBCD	File character set is HONEYWELL BCD.
EBCDIC	File character set is fixed EBCDIC.
VEBCDIC	File character set is variable EBCDIC.

The end of the input record is determined by the mode of the input file as described below:

ASCII	Terminated by a carriage-return character or record count.
SIXBIT	Determined by the header word in front of each record.
FIXSIX	Always copies the number of bytes specified by the record size.
ACL	Always copies the number of bytes specified by the record size.
BCD	Always copies the number of bytes specified by the record size.
EBCDIC	[Fixed] Always copies the number of bytes specified by the record size.
EBCDIC	[Variable] Determined by the header word in front of each record.

In general all commands may be abbreviated to any number of characters that will allow that command to be unique. However no more than six characters are checked for validity in any of the commands.

The characters "?" and "\*" may be used to denote a wild card for files on mag-tape, disk, or dectape. The character "@" denotes a command file which change will read for commands. If only an altmode is typed change will enter dialog mode.

## APPENDIX - 2

### Software

Under this head, the various programs used for K-Class classification and mapping are explained. The listings are reproduced in the latter pages.

#### 1. K-Class FOR

This program is for the K-Class classification algorithm developed by Zagalsky (1968) which gives the results in the form of a confusion matrix. This program developed by Serreyn and Nelson (1973) is modified slightly to apply for the present study.

#### Explanation of Various FORTRAN Variables of the Program

NCLASS - Number of classes of data

NSIG - Number of signals supplied for each feature

NFEAT - Number of features or Bands

P (I) - P is the apriori variability of occurrence and P(I) is the probability of occurrence of class I.

B (I,J) - B is a matrix multiplier of the feature vector X. It is calculated in the training of the classifier.

C (I) - C is a vector of constants calculated in the training of the classifier.

Cov (I,I) - Cov is the covariance matrix of attributes

AINCOV (I,I) - Inverse of the covariance matrix Cov. Inverse is calculated by calling the subroutine MATINV.

E (I) ~ E is an interim vector variable

D (I) ~ D is the decision vector and D (I) is its Ith element.

NOCL (I) ~ is the cumulative distribution of the data NOCL (2)

is the number of data for class one + class two.

Label (I) ~ It is to label the output of the classifier

NPROB ~ It generally equals 1 since new data of different features are to be used. NPROB = 2 is used if we have unequal samples for each class but wish to have equal a priori probabilities for each class.

IDEC (I,J) ~ IDEC is the confusion matrix with the correct identifications as the diagonal elements and the incorrect ones as the other elements of the matrix.

It is valuable to note that the B and C matrices are not affected by the a priori variabilities of the classes; they are based upon the sample data only. Another valuable item to note in general, which can be used to check the computer program is that

N class

$$\sum_{I=1}^N B(I,J) P(I) = 0$$

N class

$$\sum_{I=1}^N C(I) P(I) = 0$$

These equations are based upon the theory that sum of the D (I)'s must equal one since the sum of P (I)'s equal one.

### Input

The input for this program is supplied from two files; FOR 24.DAT and FOR48.DAT. FOR24.DAT consists the following four data cards.

```
10    Label (I) , I = 1,20
20    Label1 (I), I = 1,20
30    Nclass , Nfeat   Nsig
40    NOCL (I), I = 1, Nclass
```

FOR 48.DAT contains unformatted video data. The number of data should coincide with NSIG of FOR 24.DAT.

### Output

The output file is FOR 52. DAT. Besides the formatted input data, it consists of decision table, confusion matrix, percentage matrix for the classification and decision boundaries. Boundaries among the various classes is calculated by subroutine BOUND in K-dimensional space where K is number of classes.

## 2. KCLMAP . FOR

This program is for generation of a computer map based on K-Class classifier decisions. The area to be classified may be located from TOPO sheets. The co-ordinates of this area are to be converted into scan line numbers and pixel numbers. To have an idea about the number of classes present in this area may be had

from topo sheets or paper print imagery. The features suitable for the classification may be decided by feeding in the sample data in the program KCLASS.FOR. The combination of bands that gives maximum correct identification is found . After deciding the number of classes present in the area, and the suitable bands for classification, the data from the entire area to be classified is retrieved from CCT and stored in individual files. The program KCIMAP-FOR allows two bands and 9,600 signals per each bands.

The K-Class classifier decisions for individual signals are assigned K-different symbols for easy identification on the map. These symbols are to be discreetly chosen so that the various classes are distinctly visible. These symbols are supplied to the program through an array GREY declared as an integer subscripted variable. After assigning these symbols to the classifier decisions, they are stored in the array JAR. If it is desired to use higher number of signals, the capacity of JAR may suitably be altered.

It is to be remembered that the width of the physical page is 132 characters. Hence, if the width of the area to be classified i.e. difference between end pixel and starting pixel exceeds 132, the program demands amendment. By dividing the area into the two parts and classifying individually we can bypass this amendment. But, classification of the area as one unit gives best results.

### 3. Record.FOR

This program is to read a scan line of a scene. Each line is a record on the CCT. CCT contains 3 files viz. Tape Directory, Tape Header and Video Data. If nth line is to be retrieved, the first two files and  $4(n-1)$  records one to be skipped. This is because the tape is in BIL (Band Inter Leaved) format.

This program reads a record of CCT and then processes the data (from Binary to ASCII). It picks up 36 bits at a time (a WORD) and then it divides into 4 bytes (pixels). The divisive constants are as follows:

bits/bytes:	0	8	17	26	35
constants:	$2^{**4}$	$2^{**12}$	$2^{**20}$	$2^{**28}$	

This processed data are reflectance levels that range from 0 to 255. If a particular gray level is shown negative, the true level is equal to  $(256 + \text{gray level})$ .

The divisive constants discussed above are valid for 36-bit word machines like DEC series. For 32-bit word machines, the constants will correspondingly be  $2^{**24}$ ,  $2^{**16}$ ,  $2^{**8}$  and  $2^{**0}$  (i.e. 1).

#### 4. PIXEL.FOR

If a good number of grey levels are to be noted in a record then the above program may be used. On the other hand, if the level of one pixel is to be noted, the program PIXEL.FOR may be used. This is a modified program of RECORD.FOR. After execution of this program, the user has to type in the pixel number whose grey level is required. The output is from the file PIXEL.DAT. The output also contains grey levels of five preceding and five succeeding pixels of the current one. This program counts the length of initial zero fill and adds it to the pixel number supplied.

#### 5. PART.FOR

For classification purpose, one may have to retrieve a part of the scene. For this purpose, this program may be used to retrieve a part of the record. A file with extension MIC may be used for storing the data and execution of the program if it is desired to retrieve a large number of records.

#### 6. DENSITY.FOR

This FORTRAN program is for Density Slicing, a simple method for classifying the data based on their grey levels. If the range of the grey levels for a particular class is definitely known, then this method is very effective though it is a primitive method.

This Density Slicing method is synonymous to HIGHLIGHTING in Image Processing where a contour level and Interval is fed in to see the highlighted feature on the video screen. The program DENSTY.FOR is an interactive program where under execution, the user has to supply the number of classes he intends to classify, the characters to represent them, contour level and interval for each class and size of the input matrix sequentially. The output is stored in Map 1. Dat to Map 8. Dat. As cautioned previously, the user has to bear in mind that the maximum width of the output from line printer is 132. So, if the width of input matrix exceeds this number, more than one output files are to be specified. According to this program, if the width of the matrix is 480, the user has to specify that  $480/120 \approx 4$  files are required for output. This is done during interaction.

## 7. LINPIX. FOR

The ground co-ordinates, latitude and longitude of a point will be substituted by scan line number and pixel number on the imagery. So, for finding out the corresponding line and pixel number of a particular ground point, its latitude and longitude are to be precisely noted from topographic maps. These are fed in as input to get the scan line and pixel number. The program consists constants obtained from solving the eight equations that have six unknowns. These constants are valid only for a particular scene.

## 8. SORT. PAS

The line number and pixel numbers obtained from above program are to be processed before retrieving the data i.e. they are to be arranged in ascending order in order to facilitate the retrieval. This program also gives the number of records to be skipped at each stage, the scan line number division and Record number division. This data will be extremely helpful when particularly a large number of records are to be retrieved. The scan line division, Record number division obtained from the program should tally with those of the retrieved one.

## 9. PLOT. FOR

This is a graphics program written in FORTRAN that uses General Purpose Graphic System (GPGS) subroutines, for generating graphs or scatter diagrams.

## 10. FIG. PAS

This is a pascal program for generation of a line printer picture of an area by feeding in the grey levels as input. The output will be in 32 levels whereas the input data will be in 256 levels of intensity. The characters for representing the levels is a difficult task and so needs careful design.

PROGRESSIVE CLASS FOR

PROGRAM FOR K-CLASS CLASSIFICATION BASED ON THE  
ALGORITHM GIVEN BY G.D. NELSON, GEORGE SENSING INSTITUTE, SOUTH  
DAKOTA. THE ALGORITHM CAN BE USED FOR CLASSIFICATIONS UP TO  
20 CLASSES, 20 FEATURES AND 99,394 SIGNALS.

## DEFINITION OF THE PARAMETERS

**CLASS NUMBER OF CLASSES**

**THE HISTORY OF THE CONFEDERATE STATES OF AMERICA**

1980-1981  
SCHOOL OF LIBRARY  
SCIENCE

<sup>1</sup> If quality is  $\lambda$ , the classes have equal importance.

THE PROBABILITY OF A CLASS OCCURRING IS DETERMINED BY THE NUMBER OF SIGNS IN EACH CLASS.

THE UNCLASSIFIED APRAXS ARE AS FOLLOWS:

X(CLEART)	X(CHEAT)	YE(CHEAT)
Y(X(CHEAT),HEAT)	X(CHEAT)	Y(X(CHEAT),HEAT)
X(X(CLASS,HEAT))	COV(CLASS,HEAT)	(INC)X(CLASS,HEAT)
Y(CLASS,HEAT)	X(CLASS,HEAT)	Y(CLASS,HEAT)
X(CLASS)	(NCLASS)	D(CLASS)
X(CLASS)	P(CLASS)	F(CLASS)
X(CLASS)	AN(CLASS)	
X(CLASS)	AV(CLASS)	
TOP(CLASS,NCCLASS)	TERROB(TER)	
DATA(SIG,HEAT)	DRUN(HEAT)	

M A J S E R O G R B A M

NPROB=1  
CALL KGASS(NPROB)  
STOP  
END

**SUBROUTINE KCLASS STARTS**

```

SUBROUTINE KCLASS(NPROB)
COMMON AL(20),AH(20),AJ(20),AN(20),
         B(20),D(20),E(20),F(20),P(20),I1(20),
         T(20),PA(20,20),PC(20,20),LABEL(20),LABEL1(20)
COMMON DB(20),CA(20),BI(20)
COMMON IDEC(20,20)
COMMON XXT(20,20),XT(20,20),COV(20,20),MINCOV(20,20)
COMMON XBAR(20,20),Y(20,20),YA(20,20),B(20,20)
COMMON XA(20),NEWX(20),YC(20),YE(20),XC(20)
COMMON ND(20)
FORMAT(15X, 'NUMBER OF SIGNALS IN CLASS (',I1,') = ',I4,/)
FORMAT(/)
FORMAT(20A4),
FORMAT(15X, 'IC K J THE D(I) ARE ')
FORMAT(15X,15F7.3),
FORMAT(15X, 'THE COVARIANCE MATRIX ')
FORMAT(15X, 'INVERSE OF THE COVARIANCE MATRIX ')
FORMAT(15X, 'THE CORR. COEFFICIENTS RHO(I,J) ARE ')
FORMAT(15X, 'DIFF BET MEANS OF CLASS I+KK,I=1,I3, KK=1,I3)
FORMAT(15X,10F11.5)
FORMAT(15X, 'THE MATRIX C IS (',/),
FORMAT(15X, 'DIFF BET MEAN SQUARED IN SAME CLASSES ')
FORMAT(15X, 'THE STANDARD DEVIATIONS ARE ')
FORMAT(27X,13X,15F7.2),
FORMAT(27X,13X,15F7.2),
FORMAT(15X, 'PERCENT CORRECTLY IDENTIFIED OVERALL')
FORMAT(15X,20A4)

```

```

4 7657 FORMAT(15X,' PERCENTAGE MATRIX FOR ABOVE CLASSIFICATION')
5 8011 FORMAT(1H,' MEAN VECTOR OF ALL CLASSES',I15)
6 8051 FORMAT(1H,' MEAN VECTOR OF CLASS I=',I3)
7 8052 FORMAT(1H,' X(I,J) T= ',I3)
8 80193 FORMAT(1H,' THE MATRIX A IS I',//)
9 8060 FORMAT(1H,' 15X,(1IF11.5)')
10 9000 FORMAT(1H,' 39X,(CONFUSION MATRIX ',/,' 39X,15(1H-))')
11 9001 FORMAT(1H,' 26X,I3,6X,I3,11(4X,I3))')
12 9003 FORMAT(415)
13 9004 FORMAT(1H,' //,15X,BHNCLASS= ,I3,8H NFEAT= ,I3,7H NSIG= ,I3
14 184 NPROB= ,I3)
15 9005 FORMAT(1H,' 27X,'CLASS 1 2 3')
16 9007 FORMAT(1H,' 27X,'CLASS 1 2 3 4')
17 9020 FORMAT(1H,' 27X,'CLASS 1 2 3 4 5')
18 9009 FORMAT(1H,' 27X,'CLASS 1 2 3 4 5)
19 9011 FORMAT(1H,' 27X,'CLASS 1 2 3 4 5
20

21 9012 FORMAT(1H,' //,27X,'CLASS 1 2 3 4 5
22 16 9008 FORMAT(1H,' 14X,'PROBABILITIES= ',11F9.3)
23 9021 FORMAT(1H,' //,15X,'NO. OF MISCALCULATIONS ',F3.0)
24 822 FORMAT(1H,' //,15X,' THE SIGNALS IN CLASS ',I2,', ARE I',/0
25 9021 NPRE=1
26 READ 48
27 CONTINUE
28
29 C
30 READ IN THE NUMBER OF CLASSES , NUMBER OF FEATURES AND OF SIGNALS
31 READ(24,9006)(LABEL(I),I=1,20)
32 NRIT(52,20000)(LABEL(I),I=1,20)
33 FORMAT(1H,' //,20X,20A4)
34 READ(24,9006)(LABEL(I),I=1,20)
35 NRIT(52,10000)(LABEL(I),I=1,20)
36 FORMAT(1H,' //,15X,'THE CLASSES ARE I',/,' 20X,20A4)
37 READ(24,1NC/ASS,NFEAT,NSIG)
38 READ(24,*)(NCL(CL),I=1,NCLASS)
39 NRIT(52,9004)(NCLASS,NFEAT,NSIG,NPR)
40 ANS1=NSIG
41 BB=1.0/ANSIG
42 C
43 SET ARRAYS AND COUNTERS TO ZERO
44 DO 200 I=1,NCLASS
45 DO 200 J=1,NFEAT
46 XB(I,J)=0
47 200 XBAR(I,J)=0.0
48 DO 201 J=1,NFEAT
49 XB(J)=0.0
50 DO 202 I=1,NFEAT
51 DO 202 J=1,NFEAT
52 XENX(J)=0
53 KXT(I,J)=0.0
54 NCLASS=NCLASS
55 DO 204 I=1,NCLASS
56 I1(I)=0
57 A(I)=0.0
58 B(I)=0.0
59 ICOOUNT=0
60 JJ=1
61 NRIT(52,822)JJ
62
63 C
64 READ DATA CARDS
65
66 10 CONTINUE
67 ICOOUNT=ICOOUNT+1
68 A(1)=D(48,1)(K())
69 A(1)=E(52,22)(X(I),I=1,NFEAT)
70 FORMAT(20X,4F10.2)
71 IF(ICOOUNT.EQ.NCL(JJ))K=JJ
72 K=K+1
73 IF(ICOOUNT.EQ.NCL(JJ) .AND. ICOOUNT.LT.NSIG)NRIT(52,822)K11
74 COUNT NO. OF SIGNALS IN CLASS I

```

```

C1430 C
C1440 I1(K)=I1(K)+1
C1450 DO 11 J=1,NFEAT
C1460 XBAR(J,J)=XBAR(K,J)+X(J)
C1470
C1480 X
C1490 AND COMPUTE CLASS MEANS
C1500 X
C1510 100 COMPUTE X TIMES X TRANSPOSE
C1520 DO 600 IU=1,NFEAT
C1530 DO 650 J=1,NFEAT
C1540 XXT(IU,J)=XXT(IU,J)+X(IU)*X(J)
C1550 IF (IXCOUNT.EQ.0) XXT(JJ)=J*J+
C1560 IXCOUNT=IXCOUNT+1,XXT(JJ),JJ=JJ+1
C1570 CONTINUE
C1580 X
C1590 X ESTIMATE THE PROBABILITY OF OCCURENCE OF EACH CLASS
C1600 DO 18 I=1,NCLASS
C1610 AI(I)=I1(I)
C1620 C1630 C1640 18 COMPUTE
C1650 ARI1E(57,7656)(LADEL(I),I=1,20)
C1660 ARI1E(57,222)
C1670 DO 144 J=1,NCLASS
C1680 ARI1E(57,133),JB,J1(JBC)
C1690 DO 145 COMPUTE
C1700 DO 101 I=1,NCLASS
C1710 AI(I)=I1(I)
C1720 AI(I)=I./AI(I)
C1730 DO 102 I=1,NCLASS
C1740 DO 402 J=1,NFEAT

C1750 402 XBAR(1,J)=XBAR(1,J)*AI(I)
C1760 XBC(J)=XBC(J) + XBAR(1,J)
C1770 COMPUTE MEAN MATRIX
C1780 ACCLASS=NCCLASS
C1790 C
C1800 500 DO 520 I=1,NFEAT
C1810 XBC(J)=XBC(J)/ACCLASS
C1820 C
C1830 COMPUTE AVERAGE OF X TIMES X TRANSPOSE
C1840 DO 720 I=1,NFEAT
C1850 DO 730 J=1,NFEAT
C1860 XXT(I,J)=XXT(I,J)+BB
C1870 X
C1880 COMPUTE AVERAGE OF X TIMES TRANSPPOSE OF X AVERAGE
C1890 DO 800 I=1,NFEAT
C1900 DO 850 J=1,NFEAT
C1910 XF(I,J)=C(I)*XBC(J)
C1920 X
C1930 COMPUTE SAMPLE COVARIANCE MATRIX
C1940 X
C1950 DO 840 I=1,NFEAT
C1960 801 DO 841 J=1,NFEAT
C1970 XXT(I,J)=XXT(I,J)-XF(I,J)
C1980 ESTIMATE COV
C1990 DO 130 I=1,NCLASS
C2000 AI(I)=I1(I)
C2010 AI(I)=ASIG(AI(I))
C2020 C
C2030 130 ADD ADJUST(COV,AINCov,NFEAT)
C2040 X
C2050 DO 842 I=1,NFEAT
C2060 DO 843 J=1,NFEAT
C2070 Y(I,J)=XBAR(I,J)-XA(J)
C2080 Y(I,J)=Y(I,J)/ACCLASS
C2090 Y(I,J)=Y(I,J)/NFEAT
C2100 DO 844 K=1,NFEAT
C2110 X(I,J)=Y(I,K)*Y(K,J)*INCov(F,I)
C2120 X(I,J)=X(I,J)+Y(K,J)*Y(K,I)
C2130 X(I,J)=X(I,J)/NFEAT
C2140 840 DO 845 K=1,NFEAT
C2150 X(I,J)=X(I,J)/NFEAT
C2160 8453 PRINT *, 'THE MATRIX N IS ', F,I,J
C2170 8453 PRINT *, 'I=1,NFEAT
C2170 8453 PRINT *, 'J=1,NFEAT
C2170 8453 PRINT *, 'F=1,NFEAT

```

```

(2187 54      CONTINUE
(2198 829      DO 829 I=1,NCLASS
(2209 2(I)=0.0
(2210 830 I=1,NCLASS
(2221 2(J)=0.0
(2232 830 J=1,NFEAT
(2243 2(X(I,J))=B(I,J)*XD(J)
(2254 830 Y(I,J)=C(I,J)+YC(J)
(2265 830 WRITE(52,8058)
(2276 830 WRITE(52,8060)(C(I),I=1,NCLASS)
(2287 830 CONTINUE
(2298 830

```

### CLASSIFICATION OF TRAINING SAMPLES

```

(2309 4113      WRITE(52,4113),
(2320 4113      FORMAT(' ',35X,'DECISION VECTORS',//)
(2331 10003      DO 10003(1) 10004,10005,10006,10007,10008),NCLASS
(2342 10008      ARIT(52,4116); GO TO 777
(2353 10004      WRITE(52,4116); CO ID 777
(2364 10005      WRITE(52,4111); GO TO 777
(2375 10006      WRITE(52,4112); GO TO 777
(2386 10007      WRITE(52,4114); GO TO 777
(2397 777      WRITE(52,4115)
(2408 4110      CONTINUE
(2419 4110      FORMAT(19X,61(H-))//,20X,'SAMPLE NO.',4X,'CLASS',5X,'D(1)',8X,'
(2430 4111      1D(2),5X,'DECISION',//,19X,61(H-))
(2441 4111      FORMAT(19X,61(H-))//,20X,'SAMPLE NO.',4X,'CLASS',4X,'D(1)',4X,'
(2452 4112      1D(2),5X,'D(4)',4X,'DECISION',//,19X,61(H-))
(2463 4112      FORMAT(19X,56(H-))//,19X,'SAMPLE NO.',3X,'CLASS',3X,'D(1)',3X,'
(2474 4113      1D(2),3X,'D(3)',3X,'D(4)',3X,'D(5)',3X,'DECISION',//,19X,
(2485 4114      266(1H-))
(2496 4114      FORMAT(19X,70(1H-))//,19X,'SAMPLE NO.',3X,'CLASS',3X,'D(1)',3X,'
(2507 4114      1D(2),3X,'D(3)',3X,'D(4)',3X,'D(5)',3X,'D(6)',2X,'DECISION',//,
(2518 4115      219X,70(1H-))
(2529 4115      FORMAT(19X,70(H-))//,19X,'SAMPLE NO.',2X,'CLASS',2X,'D(1)',2X,'
(2540 4115      1D(2),2X,'D(3)',2X,'D(4)',2X,'D(5)',2X,'D(6)',2X,'D(7)',2X,'
(2551 4116      2DE(1H-))
(2562 4116      FORMAT(19X,70(1H-))//,19X,'SAMPLE NO.',2X,'CLASS',2X,'D(1)',2X,'
(2573 4116      1D(2),2X,'D(3)',2X,'D(4)',2X,'D(5)',2X,'D(6)',2X,'D(7)',2X,'
(2584 4117      20(8),2X,'DECISION',//,19X,70(1H-),)
(2595 549      CONTINUE
(2606 549      JJ=1

```

```

(2627 550      IC=0
(2638 550      DO 550 KAK=1,NCLASS
(2649 550      DO 550 KAK=1,NCLASS
(2650 50      10E1(KAK,KAK)=0
(2661 50      REINIT(48)
(2672 550      CONTINUE
(2683 550      IC=IC+1
(2694 837      DO 837 I=1,NCLASS
(2705 837      E(I)=0.0
(2716 837      READ(18,*)(X(I),I=1,NFEAT)
(2727 837      DO 840 I=1,NCLASS
(2738 837      DO 840 J=1,NFEAT
(2749 837      YF(I,J)=B(I,J)*X(J)
(2750 840      E(I)=E(I)+YC(J)
(2761 840      DO 850 I=1,NCLASS
(2772 840      E(I)=E(I)-E(I)+1.0
(2783 850      E(I)=E(I)+2.0X,16,6X,15,2X,3F9,2,5X,I4)
(2794 850      E(I)=E(I)+2.0X,16,6X,15,2X,4F9,2,5X,I4)
(2805 850      E(I)=E(I)+2.0X,16,6X,15,2X,5F0,2,5X,I4)
(2816 850      E(I)=E(I)+2.0X,15,3X,15,2X,6F7,2,4X,I4)
(2827 850      E(I)=E(I)+2.0X,15,3X,15,2X,7F7,2,4X,I4)
(2838 850      E(I)=E(I)+2.0X,15,2X,BF7,2,4X,I4)
(2849 850      DO 870 I=1,NCLASS
(2850 850      E(I)=P(I)*F(I)
(2861 870      I=1
(2872 870      YF(I)=YF(I)-DCK(JJ))K=JJ
(2883 870      DMAX=0.0
(2894 870      DO 880 I=1,NCLASS
(2905 870      IF ((YF(I),GT,DMAX)) GO TO 875
(2916 870      GO TO 880
(2927 870      DMAX=D(I)
(2938 870      I=1
(2949 870      CONTINUE
(2950 880

```

```

1001  IDEC(K,J)=IDEC(K,J)+1
1002  IF ((K,00,NCLASS(J,1)),J=J,J+1)
1003  WRITE(52,900)IC,K,(D(I),I=1,NCLASS),J
1004  GO TO 73
1005  WRITE(52,900)IC,K,(D(I),I=1,NCLASS),J
1006  GO TO 73
1007  WRITE(52,910)IC,K,(D(I),I=1,NCLASS),J
1008  GO TO 73
1009  WRITE(52,911)IC,K,(D(I),I=1,NCLASS),J
1010  GO TO 73
1011  WRITE(52,912)IC,K,(D(I),I=1,NCLASS),J
1012  GO TO 73
1013  WRITE(52,913)IC,K,(D(I),I=1,NCLASS),J
1014  GO TO 73
1015  WRITE(52,914)IC,K,(D(I),I=1,NCLASS),J
1016  GO TO 73
1017  WRITE(52,915)IC,K,(D(I),I=1,NCLASS),J
1018  GO TO 73
1019  CONTINUE
1020  890  IF(JLT,ANSIG)GOTO 550
1021  CONTINUE
1022  C
1023  WRITE(52,9000)
1024  C
1025  PRINT THE CONFUSION MATRIX
1026  C
1027  10020  GO TO (10020,10030,10040,10050,10060,10070),NCLASS
1028  10030  WRITE(52,9005); GO TO 9040
1029  10040  WRITE(52,9007); GO TO 9090
1030  10050  WRITE(52,9020); GO TO 9090
1031  10060  WRITE(52,9009); GO TO 9090
1032  10070  WRITE(52,9011); GO TO 9090
1033  9090  WRITE(52,9012)
1034  CONTINUE
1035  DO 9040 JK=1,NCLASS
1036  WRITE(52,9001)JK,(IDEC(JK,J),J=1,NCLASS)
1037  CONTINUE
1038  9010  DO 5 LL=1,NCLASS
1039  T(LL)=110(LL)
1040  DO 5 J=1,NCLASS
1041  PA(LL,J)=IDEC(LL,J)
1042  PC(LL,J)=(PA(LL,J)/T(LL))*100.0
1043  CONTINUE
1044  S
1045  WRITE(52,9008)(P(I),I=1,NCLASS)
1046  IERR=0
1047  JK=1
1048  CONTINUE
1049  DO 120 J=1,NCLASS
1050  IF ((JK,00,J))GOTO 120
1051  IERR=IERR+IDEC(JK,J)
1052  CONTINUE
1053  AM(JK)=IERR
1054  IERR=0
1055  JK=JK+1
1056  IF((JK,LE,NCLASS)GOTO 115
1057  TERROR=0.0
1058  DO 125 I=1,NCLASS
1059  TERROR=TERROR+AM(I)
1060  WRITE(52,9021)TERROR
1061  PCCI=((AMSTG-TERROR)/ANSIG)*100
1062

```

```

1063  125  WRITE(52,7665)PCCI
1064  126  WRITE(52,7657)
1065  127  WRITE(52,9005)
1066  128  DO 5 LL=1,NCLASS
1067  129  WRITE(52,7654)LL,(PC(LL,J),J=1,NCLASS)
1068  130  CONTINUE
1069  6   C
1070  131  C=4PR+1
1071  132  R=8142/10
1072  133  DO 780 J=1,NCLASS
1073  134  P(IJJ)=1.0/NCLASS
1074  135  IF((XPR,LE,4PR20)GOTO 549
1075  136  CALL,3017(B,C,P,NFEAT,NCLASS),
1076  137  END
1077  780

```

```

3601      SUBROUTINE BOUND(C,P,NFEAT,NCCLS)
3602
3603      THIS SUBROUTINE COMPUTES THE BOUNDARIES OF THE NCCLS
3604      FOR THE NFEAT CLASSES.
3605
3606      DIMENSION B(20,20),P(20),D(20),D1(20)
3607      DO 100 I=1,NFEAT
3608      DO 100 J=1,NCCLS
3609      DO 100 K=1,NCCLS
3610      D(I,J)=B(I,J)*P(K)
3611      100 CONTINUE
3612
3613      DO 200 I=1,NFEAT
3614      DO 200 J=1,NCCLS
3615      DO 200 K=1,NCCLS
3616      D(I,J,K)=B(I,J)*P(K)
3617      200 CONTINUE
3618
3619      DO 300 I=1,NFEAT
3620      DO 300 J=1,NCCLS
3621      DO 300 K=1,NCCLS
3622      D(I,J,K)=B(I,J)*P(K)
3623      300 CONTINUE
3624
3625      DO 400 I=1,NFEAT
3626      DO 400 J=1,NCCLS
3627      DO 400 K=1,NCCLS
3628      D(I,J,K)=B(I,J)*P(K)
3629      400 CONTINUE
3630
3631      10 FOR I=1,15X,1 THE BOUNDARY BETWEEN CLASS 'I,X,' AND CLASS 'I,X+1'
3632      10 FOR I=1,15X,1
3633      20 FOR I=1,15X,1 DIFF(I,J)=D(I,J)
3634      20 FOR I=1,15X,1 DIFF(I,J)=D(I,J)
3635
3636      100 CONTINUE
3637
3638      RETURN
3639      END
3640
3641      ***** M A T I N V      S T A R T S *****
3642
3643      SUBROUTINE MATINV(COV,AINCOV,NFEAT)
3644
3645      THIS SUBROUTINE COMPUTES THE INVERSE OF THE SAMPLE
3646      CO-VARIANCE MATRIX
3647
3648      DIMENSION PROD(20),COV(20,20),AINCOV(20,20)
3649      ABCD=1.0*( -20)
3650      DO 100 I=1,NFEAT
3651      PROD(I)=0.0
3652      DO 200 J=1,NFEAT
3653      PROD(J)=0.0
3654      100 AINCOV(I,I)=0.0
3655
3656      AINCOV(1,1)=1.0/COV(1,1)
3657      IF(NFEAT.EQ.1)GO TO 950
3658      L=L+1
3659      LR=L+1
3660      DV=0.0
3661      DO 52 J=1,L
3662      PROD(1)=PROD(1)+AINCOV(1,J)*COV(LR,J)
3663      52 DO 41 ID=1,L
3664      DV=COV(ID)*PROD(ID)+DV*COV(LR,ID)
3665      DIFF=COV(LR,LR)-DV
3666      DIFF=ABS(DIFF)
3667      IF(DIFF.LE.ABCD) GO TO 40
3668      DO 60 I=1,L
3669      AINCOV(LR,I)=-PROD(I)/DIFF
3670      AINCOV(I,LR)=AINCOV(LR,I)
3671      60 DO 80 J=1,L
3672      AINCOV(I,J)=AINCOV(I,J) + (PROD(I)*PROD(J))/DIFF
3673      AINCOV(LR,LR)=1.0/DIFF
3674      IF(LR.GE.NFEAT)GOTO 288
3675
3676      288 CONTINUE
3677      IF(LR.GE.NFEAT)GOTO 950
3678      GO TO 39
3679      288 CONTINUE
3680      GO TO 304
3681
3682      304 DO 150 I=1,15X,1
3683      DO 150 J=1,15X,1
3684      DO 150 K=1,15X,1
3685      DO 150 L=1,15X,1
3686      DO 150 M=1,15X,1
3687      DO 150 N=1,15X,1
3688      DO 150 O=1,15X,1
3689      DO 150 P=1,15X,1
3690      DO 150 Q=1,15X,1
3691      DO 150 R=1,15X,1
3692      DO 150 S=1,15X,1
3693      DO 150 T=1,15X,1
3694      DO 150 U=1,15X,1
3695      DO 150 V=1,15X,1
3696      DO 150 W=1,15X,1
3697      DO 150 X=1,15X,1
3698      DO 150 Y=1,15X,1
3699      DO 150 Z=1,15X,1
3700
3701      150 A=1,15X,1
3702      150 B=1,15X,1
3703      150 C=1,15X,1
3704      150 D=1,15X,1
3705      150 E=1,15X,1
3706      150 F=1,15X,1
3707      150 G=1,15X,1
3708      150 H=1,15X,1
3709      150 I=1,15X,1
3710      150 J=1,15X,1
3711      150 K=1,15X,1
3712      150 L=1,15X,1
3713      150 M=1,15X,1
3714      150 N=1,15X,1
3715      150 O=1,15X,1
3716      150 P=1,15X,1
3717      150 Q=1,15X,1
3718      150 R=1,15X,1
3719      150 S=1,15X,1
3720      150 T=1,15X,1
3721      150 U=1,15X,1
3722      150 V=1,15X,1
3723      150 W=1,15X,1
3724      150 X=1,15X,1
3725      150 Y=1,15X,1
3726      150 Z=1,15X,1
3727
3728      950 150 A=1,15X,1
3729      950 150 B=1,15X,1
3730      950 150 C=1,15X,1
3731      950 150 D=1,15X,1
3732      950 150 E=1,15X,1
3733      950 150 F=1,15X,1
3734      950 150 G=1,15X,1
3735      950 150 H=1,15X,1
3736      950 150 I=1,15X,1
3737      950 150 J=1,15X,1
3738      950 150 K=1,15X,1
3739      950 150 L=1,15X,1
3740      950 150 M=1,15X,1
3741      950 150 N=1,15X,1
3742      950 150 O=1,15X,1
3743      950 150 P=1,15X,1
3744      950 150 Q=1,15X,1
3745      950 150 R=1,15X,1
3746      950 150 S=1,15X,1
3747      950 150 T=1,15X,1
3748      950 150 U=1,15X,1
3749      950 150 V=1,15X,1
3750      950 150 W=1,15X,1
3751      950 150 X=1,15X,1
3752      950 150 Y=1,15X,1
3753      950 150 Z=1,15X,1

```

This program generates a gray-scale map of the study area based on multi-class classifier decisions.

The variables names and arrays mostly stand for what they are in the `CLASS.F90` program.

This program needs amendment when the width or the input matrix exceeds 128 characters and the number of signals per each point that are supplied for classification should not exceed 3600.

The program gives the legend and other particulars like - number of pixels present and area occupied by each class.

Author : A. Suganth Mohan

Date written : 15th March, 1986.

To undergo the following:

Defining the parameters

Defining the output class

Defining the input classifier

Defining the output classifier

Main Program

Subroutine

CLASSIFICATION

STOP

END

Subroutine CLASSIFICATION starts

Subroutine CLASSIFICATION

```

      CEGGER GRAY(20), COUNT(20), COUNT(20)
      COUNT(20), AM(20), AI(20), AN(20)
      COUNT(20), BC(20), E(20), F(20), P(20), T(20)
      COUNT(20), PA(20,20), PC(20,20), LABEL(20), LABEL(20)
      COUNT(20), CA(20), BI(20), PERCENT(20)
      COUNT(20), IDEC(20,20)
      COUNT(20,20), XT(20,20), COV(20,20), MNCOV(20,20)
      COUNT(20,20), XBAR(20,20), Y(20,20), YAC(20,20), O(20,20)
      COUNT(20,20), NEWX(20), XC(20), YE(20), K(20)
      COUNT(20,20), NOCL(20)
      COUNT(20,20), JAR(20000)
      FORMATT(20A1)
      FORMATT(20A4)
      VPR(1)
      READING 48
      CONTINUE
      READ NCL, OF CLASSES, NO. OF FEATURES,
      AND NUMBER OF SIGNALS
      READ(45, 9006) (LABEL(I), I=1, 20)
      READ(45, *) NCLASS, NFEAT, NSIG
      READ(45, *) (NCL(I), I=1, NCLASS)
      READ(45, 14) (GRAY(I), I=1, NCLASS)
      COUNT(1)=0
      CONTINUE
      COUNT(1)=COUNT(1)+1
      READ(55, *) X1
      READ(57, *) X2
      IF(X1.GT.0) X1=256+X1
      IF(X2.GT.0) X2=256+X2
      X(1)=X1
      X(2)=X2
      WRITE(6, *) X1, X2
      IF((COUNT(1).GT.NSIG)) GO TO 15
      ANSIG=NSIG
      BB=1.0/ANSIG
      INITIALISE ARRAYS AND COUNTERS
      DO 200 I=1, NCLASS
      DO 200 J=1, NFEAT
      S(I, J)=0
      XBAR(I, J)=0.0
      DO 201 J=1, NFEAT
      K(J)=0.0
      DO 202 I=1, NFEAT
      DO 202 J=1, NFEAT
      NEWX(J)=0
      XT(I, J)=0.0
      ACUM(5)=NCLASS
      DO 204 I=1, NCLASS
      L1(I)=0
      LK(I)=0.0
      EX(I)=0.0
      ED(I)=0.0
      JU=1

      READING 49
      DO 797 I=1, NSIG
      JAR(I)=0
      DO 797 I=1, NCLASS
      COUNT(1)=0
      READ DATA CARDS
      CONTINUE
      COUNT(1)=COUNT(1)+1
      READ(48, *) (X(I), I=1, NFEAT)
      IF(ICOUNT.GE.NOCL(JU)) K=JU

```

KM1=K+1  
 DO J=1,NFEAT  
 KBAR(K,J)=XBAR(K,J)+X(J)  
 CONTINUE  
 TO COMPUTE MEANS OF EACH CLASS  
 AND COMPUTE X TIMES X TRANSPOSE  
 DO 600 LU=1,NFEAT  
 DO 600 J=1,NFEAT  
 XXP(LU,J)=XXP(LU,J)+X(LU)\*X(J)  
 IF (LUDLU.EQ.NCOL(J)) J=J+1  
 CONTINUE  
 TO ESTIMATE THE PROBABILITY OF  
 OCCURRENCE OF EACH CLASS  
 DO 13 I=1,NCLASS  
 AI(I)=1.0  
 PI(I)=83\*B1(I)  
 DO 13 CONTINUE  
 DO 244 JB=1,NCLASS  
 DO 244 CONTINUE  
 DO 301 I=1,NCLASS  
 AI(I)=1.0  
 AI(I)=AI(I)/NCLASS  
 DO 302 I=1,NFEAT  
 KBAR(I,J)=XBAR(I,J)+XBAR(I,J)  
 KBAR(J,J)=XB(J)+XBAR(I,J)  
 COMPUTE MEAN MATRIX  
 ACUMMISENCCLASS  
 DO 500 J=1,NFEAT  
 XB(J)=XB(J)/NCLASS  
 DO 491 I=1,NFEAT  
 DO 491 J=1,NFEAT  
 XXP(I,J)=XXP(I,J)+XB  
 DO 492 I=1,NFEAT  
 DO 492 J=1,NFEAT  
 XB(I,J)=XB(I,J)\*XB(J)  
 COMPUTE SAMPLE COVARIANCE MATRIX  
 DO 521 I=1,NFEAT  
 DO 521 J=1,NFEAT  
 DOV(I,J)=XXP(I,J)-XB(I,J)  
 ASI,J=COUNT  
 DO 130 I=1,NCLASS  
 AI(I)=ASI/J\*AI(I)  
 CALL DINV THE SUBROUTINE TO FIND THE  
 INVERSE OF THE COVARIANCE MATRIX  
 CALL DINV(V,X,AINCOV,NFEAT)  
 DO 810 I=1,NFEAT  
 Y(I,J)=XBAR(I,J)-XB(J)  
 DO 820 I=1,NCLASS  
 DO 820 J=1,NFEAT  
 DO 820 K=1,NFEAT  
 Y(AINCOV,K)\*AINCOV(K,J)  
 B(I,J)=B(I,J)+Y(AINCOV,K,J)  
 DO 53 I=1,NCLASS  
 DO 53 J=1,NFEAT  
 Y(I,J)=B(I,J)\*XB(J)  
 Y(I,J)=C(I,J)+Y(I,J)  
 DO 835 CONTINUE



```

      SUBROUTINE MAINV STARTS
      SUBROUTINE MAINV(COV,AINCOV,NFEAT)
      THIS SUBROUTINE COMPUTES THE INVERSE OF THE SAMPLE
      CO-VARIANCE MATRIX

      DIMENSION PROD(20),COV(20,20),AINCOV(20,20)
      ABCD=1.0*(-20)
      DO 100 J=1,NFEAT
      PROD(J)=0.0
      DO 200 I=1,NFEAT
      DO 200 J=1,NFEAT
      AINCOV(I,J)=0.0
      DO 300 I=1,NFEAT
      AINCOV(I,I)=1.0/COV(I,I)
      IF(NFEAT.GE.1)GO TO 950
      39
      DO 400 I=1,NFEAT
      DO 400 J=1,NFEAT
      PROD(I)=PROD(I)+AINCOV(I,J)*COV(J,I)
      DO 500 I=1,NFEAT
      DO 500 J=1,NFEAT
      PROD(I)=PROD(I)+AINCOV(I,J)*COV(LR,J)
      DO 600 I=1,NFEAT
      DO 600 J=1,NFEAT
      DIFF=COV(I,J)-LR
      DIFF=ABS(DIFF)
      IF(DIFF.GE.ABCD) GO TO 40
      DO 600 I=1,NFEAT
      AINCOV(LR,I)=PROD(I)/DIFF
      40
      AINCOV(LR,LR)=AINCOV(LR,LR)+1.0/DIFF
      AINCOV(L,R)=AINCOV(L,R)+(PROD(I)*PROD(J))/DIFF
      AINCOV(J,L)=AINCOV(J,L)+(PROD(I)*PROD(J))/DIFF
      AINCOV(L,R)=1.0/DIFF
      IF(CR.GE.NFEAT)GOTO 288
      288
      CONTINUE
      IF(LR.GE.NFEAT)GOTO 950
      290
      CONTINUE
      GO TO 304
      304
      DO 310 I=1,NFEAT
      DO 310 J=1,NFEAT
      AINCOV(I,J)=AINCOV(I,J)+AINCOV(J,I)
      310
      NFEAT=NFEAT-1
      GO TO 39
      39
      CONTINUE
      RETURN
      END

```



By Order of the Secretary of State

This program is to read a record of the CCT to get the gray level of certain pixel sets has to be fed into program while later execution.  
This program also provides the reflectance values of five pixels on either side of the wanted one.

Author: A. Durall, editor  
Date written: 1996

The Counter-Party Legend of the Journal of the Royal Phil.

THIS PROGRAM READS A COMPUTER FILE, PRINTED IN 32 X  
32 LEVELS, MAKING THE REFLECTANCE VALUES AS INPUT.

```
PROGRAM PENTADY(INPUT,OUTPUT);
VAR
    CH1 : array [0..64,0..54] of integer;
    CH2 : array [0..64,0..32] of char;
    I,J,K,L : integers;
begin
    READLN(I);
    for I:= 0 to K-1 do
        begin
            for J:= 0 to L-1 do READ(CH1[I,J]);
            READLN();
        end;
    for I:= 0 to K-1 do
        begin
            for J:= 0 to L-1 do READ(CH2[I,J]);
            READLN();
        end;
    for I:= 0 to K-1 do
        begin
            for J:= 0 to L-1 do
                begin
                    for K:= 0 to I-1 do WRITE(CH2[I,K],CH1[I,K]);
                    Writeln(CH2[I,I]);
                    end;
                end;
        end;
end.
```

#### **Parasitism** and **Pathogenesis**

THIS IS AN INTERACTIVE PROGRAM FOR MAPPING THE SURFACE FEATURES BASED ON THE DEPTH MAPS READING PICTURES EFFECTIVE FOR 10 CLASSIS. THERE IS A LIMIT ON THE LENGTH OF THE INPUT FILE AND NUMBER OF POINTS PER STEP SHOULD NOT EXCEED 960.

**APPROVED:** **RECORDED AND INDEXED:**

```
TITLECR TETRA(960), TETRA(950), GREY(100)
TETRAGER GNDP(100), LNTV(100), HPPU(100), LOWLIT(100)
OPEN{CONT}#2, DEVICE='DSK', FILE='TAPUT'
OPEN{CONT}#3, DEVICE='DSK', FILE='MAP1'
OPEN{CONT}#4, DEVICE='DSK', FILE='MAP2'
OPEN{CONT}#5, DEVICE='DSK', FILE='MAP3'
OPEN{CONT}#6, DEVICE='DSK', FILE='MAP4'
OPEN{CONT}#7, DEVICE='DSK', FILE='MAP5'
OPEN{CONT}#8, DEVICE='DSK', FILE='MAP6'
OPEN{CONT}#9, DEVICE='DSK', FILE='MAP7'
OPEN{CONT}#10, DEVICE='DSK', FILE='MAP8'
```

## TRANSACTIONS

```

TYPE 10
FORMATC, 'BUT PERMITTED INPUT IS FORMAT FREE' //,
1BX, 'TYPE IN THE NUMBER OF CLASSES FOR SLICING'
ACCEPT 1,ACLASS
TYPE 20
FORMATC8X, 'TYPE IN CHARACTERS FOR REPRESENTATION
1 OF THE CLASSSES'
ACCEPT 25,CLREVT(I),I=1,ACLASS
FORMATC10A1)

```

TO GET THE CONTOUR LEVELS AND INTERVAL OF EACH CLASS FROM TERMINAL.

D1 30 T2, /35,50  
 TYPE 40  
 FORMAT(DY, 'TYPE IS THE COUNTING LEVEL AND INTERVAL',12)  
 ACCEPT +,D,T,D(T),C(T,U))  
 INPUT(C)COUNT(D)C(T,V)(1)  
 INPUT(M1)INPUT(L1)\*INTV(1)  
 COUNTING  
 TYPE 52  
 FORMAT(DY, 'TYPE IS THE LENGTH AND BREADTH OF INPUT')  
 ACCEPT +,L,B,L(B,L)  
 TYPE 55  
 FORMAT(DY, 'TYPE IS THE NUMBER OF OUTPUT FILES')  
 ACCEPT +,N,O,N(O)

#### T<sub>0</sub>T<sub>2</sub>ΔACT(t) vs. R<sub>0</sub>D<sub>0</sub>

THE PROGRAM READS THE INPUT DATA FROM THE INPUT FILE

INPUTS FOR THE  
TRANSFORM

TO READ AND CLASSIFY THE INPUT DATA

```
INPUTS  
CONTINUE  
READ(25,*)(P1X(I),I=1,N1Y)  
INPUT(MAT)=1  
DO 70 I=1,MAT  
DO 70 J=1,N  
IF((TP1X(I),J)=0.0D0)GO TO 70,(TP1X(I),GE,0.0D0,I,J)  
100(MAT)=0,R1Y(I)  
CONTINUE
```

To transfer the results from INTMAT to output files  
for getting the line printer map.

```
MULIT=6  
M=1  
N=M+19  
DO 80 I=1,MULIT  
WRITE(NUMLIT,90)(INTMAT(J),J=N,M)  
FORMAT(12,A1)  
NUMLIT=MULIT+1  
M=M+1  
N=M+19  
CONTINUE  
IF((LBOOE,LT,MLE)) GOTO 80  
STOP  
END
```

$\mathbf{P}_{\text{I},\text{II}}/\mathbf{P}_{\text{I},\text{II}} \approx 10^{-5}$  ( $\mathbf{P}_{\text{I},\text{II}}$  =  $10^{-12} \text{ W/m}^2$ )

This program reads a record at the CRT but the output will be only a part of it.

Not to be printed.

date written: 10-5-1966.

## To write later

$\text{NET}_1 \in \mathcal{B}(S^1, \pi) \cap \mathcal{C}^{\infty}(M_1 \times \{x_1 = 0\}, \mathbb{R})$ .

3102

10

CB-1986-M-MOH-COM